Green Neighbors, Greener Neighborhoods: Peer Effects in Residential Green Investments*

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Abstract

Utilizing a nearest-neighbor research design, I find that households exposed to green neighbors within 0.1 miles are 1.6 times more likely to make their homes green within a year than unexposed households. The exposure also increases the likelihood of multi-property owners certifying their faraway secondary properties green, emphasizing that information from neighbors, not neighborhood characteristics alone, drives the effect. While higher green home prices, electricity savings, and regulatory incentives strengthen the peer effect, pro-environmental household preferences do not. An information-cost-based discrete choice model explains the findings and suggests that aligning green subsidies with peer effects can accelerate residential green investments.

JEL Classification: D12, D14, G51, Q54, R23, R31.

Keywords: Household Residential Green Investments; Causal Neighborhood Peer Effects; Nearest-Neighbor Design.

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Investments in efficient and renewable residential technologies have the potential to reduce the energy and carbon impact of the residential sector on the environment. Often referred to as "residential green investments", a broader uptake of such technologies by households may play an essential role in addressing climate change, since this sector accounts for nearly 20 percent of annual greenhouse gas (GHG) emissions (EPA (2024)). Beyond the environmental benefits, these investments often come with regulatory incentives, lower utility costs, and also higher house prices in some markets (Dodge Data & Analytics (2020), p. 16, 22). Yet almost 98 percent of single-family homes in the US remain non-certified for energy efficiency as of 2022. Information-related issues among households are cited as a key barrier limiting the wider adoption.[1] These issues stem from limited awareness about opportunities for such investments, uncertainty about the associated costs and benefits, and insufficient expertise regarding the underlying green technologies.[2] This paper is a step towards understanding how households overcome these informational challenges to invest in residential green technologies by utilizing their peer networks.

Peer network has been shown to be an important source of information for households in decisions such as refinancing and mortgage repayments (Maturana and Nickerson (2019), McCartney and Shah (2022), Gupta (2019)), property investments (Bayer, Mangum, and Roberts (2021), Bailey et al. (2018)), and consumption (Bailey et al. (2022)). When it comes to investing in residential green technologies, households may find their peer networks even more important due to a challenging informational environment. First, there are no well-developed advisory markets or intermediaries for such investments, limiting the information generally available to the households. Second, the relatively low adoption of green technologies results in scarce practical information, making already-adopting peers a particularly relevant source of information. Third, such investments often receive limited attention in popular discourse including news and media, making it harder for households to discover and understand them. Motivated by these, I examine in this paper the causal effects of neighbor peers on the decision of households to invest in residential green technologies certifying their homes green.

[1] See Matisoff, Noonan, and Flowers (2016), Howarth and Andersson (1993), and Ramos et al. (2015) and Giraudet (2020).

[2] Green technologies refer to the features that allow a home to meet specific environmental and sustainability standards. These features include energy and water efficiency, durability, indoor air quality etc. Installing them requires examining home's geometry, construction materials, compatibility etc., and area's microclimate, utility tariff structure, zoning laws etc. (CEC (2008)).

Beyond the informational environment, residential green investment decisions are different from other household decisions commonly examined in the peer effect literature in an important manner. Decisions such as applying for mortgages, refinancing, and financial investments are private goods, whereas the environmental benefits such as reduced GHG emissions arising from residential green investments are public in nature, making room for policy interventions. Utilizing a simple discrete choice model with social interactions following Brock and Durlauf (2001), I demonstrate that adoptions of these technologies could be widened, in line with the socially optimum level, by designing policy interventions that take into account the socioeconomic determinants of peer effects. In a departure from prior peer effect studies, I also use this green investment setting to study how financial and pro-environmental motives of households shape the peer effects.[3]

I begin the analysis with a theoretical discrete choice model under social interactions in which households imperfectly observe neighbors' green investment decisions. They derive utility from adopting residential green technologies while incurring installation and information acquisition costs. They observe neighbors' decision imperfectly. Households require two types of information—general information about the technologies (awareness) and specific information about their neighborhoods and homes. As more neighbor peers adopt these technologies, social interactions with them raise awareness of focal households about the technologies and lower their general information costs. Furthermore, in areas where peers find that the adoptions are on average financially beneficial, information from them also aids the focal households with localized neighborhood- and home-specific information, reducing their specific information costs.[4] These forces result in two key implications. First, information transmission from neighbors influences focal household's decision to adopt the green technologies. I refer to it as the *green peer effect*. Second, the peer effect is heterogeneous. It is stronger in areas where the adoptions are financially beneficial. I test these implications using novel data on US households' investments in residential green technologies.

[3] Residential green investments studied in this paper are on average financially beneficial, a finding opposite to Fowlie, Greenstone, and Wolfram (2018), who report negative returns on energy efficiency investments undertaken by low-income households in Michigan under a subsidized program. See Section VI.D for more details.

[4] In areas where adoptions are not beneficial, neighbors convey so. Information from them is devoid of specific information. Therefore, focal households' cost of specific information is not reduced. See Section I for details.

To obtain causal estimates of neighborhood peer effects, I adopt a nearest-neighbor research design similar to Bayer, Mangum, and Roberts (2021), Bayer et al. (2022), McCartney and Shah (2022), and McCartney, Orellana-Li, and Zhang (2024). I estimate the effect of residential green investment decisions of hyper-local neighbors located within 0.1 miles on the decisions of focal households to do the same, while adjusting for the effect of such investments occurring within the slightly broader neighborhoods of 0.3 and 0.5 miles. While a random assignment of neighbors would be ideal for causal inference, the nearest-neighbor design mimics a quasi-random neighbor assignment due to the thinness of the single-family housing market. The ability of households in this market to choose a specific property within a 0.1-mile area—conditional on having decided to live in the slightly broader neighborhood of 0.3 and 0.5 miles—is particularly constrained due to the limited availability of for-sale homes at the time of purchase. I argue that neighborhood sorting alone does not explain the peer effect, since the magnitude of peer effect does not vary across areas differing in housing supply.

This research design also mitigates the issue that the peer effect is driven by a common exposure of neighboring households to some unobserved characteristics (Manski (1993)). To the extent that the effect of such characteristics is continuous with distance, the inner-outer ring comparison differences out their effect and identifies the discontinuous jump in the decision between the rings. Adding credence to this idea is the finding that several observable demographic and property characteristics have been shown to remain broadly similar within 0.5-mile neighborhoods (Bayer, Mangum, and Roberts (2021)). Furthermore, I provide direct evidence subsequently that peer effects are not driven by neighborhood-specific unobserved characteristics by evaluating effects of immediate neighbors on decisions of multi-property owners to green certify their secondary properties in faraway neighborhoods.

This research design is particularly suited to isolate the key mechanism of this paper, information transmission, from other characteristics such as race, income and education, because while these characteristics do not vary drastically from 0.1 miles to 0.3 and 0.5 miles, information transmission through neighborly social interaction likely decays sharply over such distances.

I address the issue of measuring household investments in residential green technologies uniformly and unambiguously, at a large scale, by assembling a novel dataset on green certifications of single-family homes from Green Building Registry

(GBR). The certification evaluates whether a home has features that meet specific environmental and sustainability standards, such as energy and water efficiency, durability, indoor air quality etc. Section II describes the process in detail. I define a home as green certified in the quarter it receives a green certificate that shows that it is more efficient than the average US home. This definition reflects both (i) the intention of households to invest in residential green technologies, since the certification process is initiated by households and requires a series of interdependent investment decisions ranging from energy efficiency to water conservation; and (ii) the green nature of the investment, since it implies compliance with elaborate certification standards, such as CEC (2008).[5]

I measure green exposure of a focal household quarterly as the rolling sum over the past four quarters of the number of neighbors within $d = 0.1, 0.3,$ and 0.5 miles who for the first time green certified their homes. Using the nearest-neighbor research design, I find that one additional green neighbor within 0.1 miles raises the probability of a household to also become green by 1.6 times within the subsequent year, consistent with the implications of the model. This effect is sizable relative to the reported peer effects of 8% for property investments (Bayer, Mangum, and Roberts (2021)) and 3.3% for refinancing (McCartney and Shah (2022)). Also it is robust to the inclusion of granular fixed effects for spatial (zip code), temporal (year-quarter), and a host of property and neighborhood controls.

Focal households' imperfect observability of neighbors' decisions gives rise to an error term in the utility function. Assuming the error term to be Gumbel and type I extreme value distributed, as common in discrete choice models (McFadden (1984), Brock and Durlauf (2001)), results in a hump-shaped relation between the marginal probability of adoption and the number of already-adopting neighbors. See Section I for details. The data confirm this relation, indicating that as neighboring adoption increases, the influence of neighbor peers in providing information to focal households first strengthens—when relevant knowledge is scarce—and then diminishes once such information becomes more widespread.

[5] In Section VI.A, I provide evidence that green certifications represent real investments in homes. First, green-certified homes are more likely than non-green-certified homes to have received building permits within one year prior to the certification (Table IX). Second, aggregate number of certifications in a zip code is positively correlated with residential energy tax credits, which are claimable from the Internal Revenue Service (IRS) only for verified residential green improvements (Table X).

I conduct a series of tests to rule out common alternative explanations. I show that green certifications reflect real investments in homes, and the peer effect does not exist in general non-green home improvements and is not driven by builders' decisions.

I draw on the high granularity of the data to isolate the role of information transmission from neighborhood-specific unobserved characteristics, such as contractor availability or geo-spatial features, in driving the peer effect. I do so by focusing on the green investments by multi-property owners (MPOs) in their secondary property located in faraway neighborhoods. I find that the 0.1-mile green exposure of MPOs around their primary home (where they currently live) has a positive effect on their decision to make their secondary property green when there is high similarity (top quartile) between their secondary property and the neighboring properties within 0.1 miles around their primary home. This effect does not exist in the bottom quartile of the similarity. These findings emphasize that MPOs utilize information from their immediate green neighbors to adopt green technologies in their faraway secondary properties, and the neighborhood-specific characteristics do not play a major role in driving the peer effect.

Two additional findings emphasize the role of information flow in driving the peer effect. First, the focal households are more likely to choose the same green certificates, similar investment specifications, and the same lenders as their immediate neighbors (within 0.1 miles) compared to those slightly farther away (0.1 to 0.5 miles), shedding light on the *type* of information sought by the focal households. Second, the green-peer effect is stronger in areas with a higher strength of local community interactions, characterized by stronger social ties and fewer non-owner-occupied properties.

As previously mentioned, the model predicts that the peer effect is stronger in areas where green homes enjoy additional potential benefits. Consistent with this, I find that the green-peer effect is stronger in counties experiencing higher house prices for green homes and above-median number of regulatory financial incentives to invest in residential green technologies, and also in areas that have above-median potential for retail electricity savings (proxied by marginal prices).

I also incorporate household green preference in the model as a fundamental idiosyncratic gain in utility from green investment, which is independent of neighbors. This independence implies that while the number of adoptions is correlated with the number of households with such preference, the strength of the peer effect is not. I indeed find that the percentage of green homes in an area is positively correlated with the fraction of households with green preference (proxied by county-level climate opinion and zip code-level electric vehicle usage). At the same time, the green peer effect is not statistically different across areas with a high and low fraction of such households. This together with the finding that peer effects are stronger in areas where green homes enjoy potential financial benefits implies that financial benefits play a larger role than the green preference in shaping the green peer effect.

The model also delivers a prediction regarding policy implication in presence of peer effects. Since a focal household does not internalize its own (positive) effect on subsequent adoption decisions of yet-to-adopt neighboring households, the adoptions in aggregate would be lower than the level achieved by a social planner, who internalizes this individually-non-internalized effect. This socially optimum level can be restored by providing subsidies to households for adopting the technologies. Further analysis of the optimal subsidy reveals that under low peer effect environment (as prevalent currently in the US according to my empirical estimates), allocating the subsidies to areas with stronger peer effects would deliver more bang for the buck. I however find that the number of regulatory incentives is not higher in areas that I estimate to have stronger peer effects.

Contribution and Related Literature: Methodologically, I build on the growing literature that uses a nearest-neighbor research design to estimate causal neighborhood peer effects in household decisions, such as investment properties (Bayer, Mangum, and Roberts (2021)), relocation (Bayer et al. (2022)), refinancing (McCartney and Shah (2022)), and home sales (McCartney, Orellana-Li, and Zhang (2024)). This paper is the first to use a nearest-neighbor design to study causal peer effects in investments by households in residential green technologies and yields new insights into drivers and obstacles in wider adoption of such technologies. This paper is also the first to apply the nearest-neighbor design on a national scale, which is a computationally intensive task.[6] Moreover, beyond identifying the role of information transmission in peer effects, this paper leverages the institutional features of housing markets to show that "keeping-up-with-the-Joneses" motive or conspicuous consumption preferences are unlikely to be the dominant mechanism.

My paper primarily contributes to the literature on information-induced peer effects in household financial decisions. Peer effects have been shown in stock

[6] Nearest-neighbor design in previous studies has been implemented on smaller geographies, such as one county (McCartney and Shah (2022)), a few metropolitan statistical areas, (Bayer, Mangum, and Roberts (2021)) or one state (Bayer et al. (2022)).

market participation (Hong, Kubik, and Stein (2004), Brown et al. (2008)), property investment (Bayer, Mangum, and Roberts (2021), Bailey et al. (2018)), refinancing (Maturana and Nickerson (2019), McCartney and Shah (2022)), mortgage repayments (Gupta (2019)), and consumption (Bailey et al. (2022)). I add to this literature by showing that households use information from their neighbor peers to make informationally-complex decisions to adopt green technologies in their residential properties. A few studies have documented peer effects in solar panels and residential landscaping (Bollinger and Gillingham (2012), Graziano and Gillingham (2015), Rode and Müller (2021), Bigler and Janzen (2023), Bollinger, Burkhardt, and Gillingham (2020)), but they have necessarily done so in limited geographic contexts and limited property and feature types. My paper however examines the green technologies that are multidimensional and applicable to nearly all property types and differs significantly in mechanism, empirical design and scope, and in providing a theoretical explanation for the peer effect.[7] My paper also complements Qiu, Yin, and Wang (2016) who document spillovers in green certifications of institution-owned commercial buildings. Insights from my paper are significantly distinct since households are more likely to suffer from informational issues and financial constraints. Moreover, my paper is related to the literature on home improvement (Montgomery (1992), Choi, Hong, and Scheinkman (2014), Melzer (2017)) and specifically focuses on an environmentally-focused form of home improvement.

The paper also contributes to the literature on households' pro-environmental decisions. While environmental concerns have been shown to influence their decisions on retirement portfolio (Anderson and Robinson (2019)), investment portfolio (Choi, Gao, and Jiang (2020), Fisman et al. (2023), Ilhan (2020)), and consumption (Gargano and Rossi (2024)), this paper focuses on their decisions to invest in residential green technologies that directly reduce GHG emissions. Literature has highlighted the debate between pro-environmental preferences and financial motives in driving house-

[7] My paper diverges from these other papers mentioned above in several aspects. First, unlike these papers, which document the presence of peer effects, my paper additionally provides a theoretical explanation for the green peer effect and identifies the underlying mechanism. My paper also diverges in focusing on the role of potential financial benefits and housing market conditions. Second, my paper uses a nearest-neighbor design for causal estimates in a hyper-local setting, as opposed to the OLS and IV methods in Bollinger and Gillingham (2012), Bigler and Janzen (2023), and Bollinger, Burkhardt, and Gillingham (2020). Third, whereas my paper documents that it is information transmission rather than "keeping-up-with-the-Joneses" motive or conspicuous consumption preferences that drives the green peer effect, Bigler and Janzen (2023) do not discuss the underlying mechanism. Moreover, my paper also differs from Bigler and Janzen (2023) in analyzing the role of both demand-side factors (such as financial motives and green preferences) and supply-side factors (such as regulatory incentives).

holds' sustainable investments (Riedl and Smeets (2017), Hartzmark and Sussman (2019), Barber, Morse, and Yasuda (2021), Bauer, Ruof, and Smeets (2021), Giglio et al. (2025)). I document that investments in residential green technologies are financially beneficial and financial motives play a larger role than green preferences in driving peer effects.

The rest of the paper is organized as follows. Section I presents the theoretical model. Section II describes the institutional background of residential green investments and certification, and Section III describes data and presents summary statistics. Section IV illustrates the empirical strategy. Section V is centered on the results. Section VI provides supplementary results, and Section VII concludes.

I. Theoretical Framework

To illustrate the peer effect mechanism, I follow Brock and Durlauf (2001) to develop a discrete choice model under social interactions. In the model, households incur information cost to invest in residential green technologies and neighbor peers reduce this cost, leading to peer effects. The implications of the model guide the subsequent empirical analysis.

A. The Model

A household i faces a decision on whether to make investment in his or her house to adopt green technologies $g_i \in \{0,1\}$, where $g_i = 1$ represents the adoption. $\boldsymbol{g} = (g_1, \ldots, g_I)$ denotes the adoption choices of households of population I. $\boldsymbol{g}_{-i} = (g_1, \ldots, g_{i-1}, g_{i+1}, g_I)$ denotes the decisions of all households other than i. The utility of household i from making the investment consists of three components, described in detail below:

$$u_i(g_i) = \text{Payoff}_i(g_i) - \text{Cost}_i(g_i, \mu_i^e(\boldsymbol{g}_{-i})) + \varepsilon_i(g_i). \tag{1}$$

A.1. Payoff

The payoff of adopting residential green technologies ($g_i = 1$) is an increase in household utility arising from private monetary benefits (e.g., lower electricity bills). Following Manski (1993), Brock and Durlauf (2001) and Brock and Durlauf (2007), and Bhattacharya, Dupas, and Kanaya (2024), I assume this increase $\Pi_i(\cdot)$ to be linear in household and neighborhood characteristics $n = (1, \ldots, N)$ as follows:[8]

$$\text{Payoff}_i(g_i) = [\Pi_i(\cdot)]g_i, \text{ where } \Pi_i(\cdot) = \sum_{n=1}^{N} \beta_n x_i^n \, . \tag{2}$$

A.2. Cost

Households incur two types of cost to adopt residential green technologies. The first is an explicit private adoption cost $C_i^P(\cdot)$ arising from cost of material, labor, maintenance etc. This cost is linear in household and neighborhood characteristics:

$$C_i^P(g_i) = [C_i(\cdot)]g_i, \text{ where } C_i(\cdot) = \sum_{n=1}^{N} \gamma_n x_i^n \, . \tag{3}$$

The second type of cost is an implicit cost of acquiring information, which has been argued to be a key barrier to the adoption (Matisoff, Noonan, and Flowers (2016), Howarth and Andersson (1993), Ramos et al. (2015), Giraudet (2020)). It models the idea that households would need to become aware about the technologies and assess the potential net benefits to make the adoption decision.

This information cost consists of two components. The first component C_i^η is the cost of becoming aware about the existence of the technologies (Xiong, Payne, and Kinsella (2016), Rogers, Singhal, and Quinlan (2014)). This cost decreases with an increase in the number of already-adopting neighbors through peer sensitivity term $\nu_1 > 0$, because they act as a source of this general information for focal households. This cost takes the following form:

$$C_i^\eta(g_i, \mu_i^e(\boldsymbol{g}_{-i})) = (F_1 - \nu_1 m_i)\, g_i; \text{ where } m_i = \mu_i^e(\boldsymbol{g}_{-i}) = E[\boldsymbol{w}_i \boldsymbol{g} | \boldsymbol{X}] = \boldsymbol{w}_i \boldsymbol{m}. \tag{4}$$

F_1 represents the cost households would need to incur to acquire the general information in the absence of peers. m_i is the expectation that household i places on the adoption decisions of all neighbor peers $\boldsymbol{g}_{-i}$ conditional on their observable exogenous characteristics $\boldsymbol{X} = (\boldsymbol{x}_i', \ldots, \boldsymbol{x}_I')'$. The cost depends on the expectations of peers' decisions rather than the realizations, because focal households do not fully observe the adoption decisions of their neighbors. $\boldsymbol{w}_i = (w_{i1}, \ldots, w_{iI})$ is an I-dimensional row vector identifying household i's neighbors, such that w_{ij} is one if household j lives in the same neighborhood as household i and zero otherwise. Moreover, self-influence is not allowed ($w_{ii} = 0$). $\boldsymbol{m}$ is an I-dimensional column vector representing expectations of households' adoption decisions conditional on characteristics $\boldsymbol{X}$.

[8] This term is also similar to the private utility in Lambotte et al. (2023), individual productivity in Lee et al. (2021), and individual effects in Boucher and Bramoullé (2020).

The second cost component C_i^{ψ} is incurred by households to acquire specific information about the technologies that is idiosyncratic to their underlying home and the broader neighborhood, in order to estimate the net realizable potential benefits.[9] The already-adopting neighbor peers also play a role in reducing this cost of specific information. As more neighbors adopt, they aid the focal household in the process to search reliable suppliers, lenders, and appropriate technology type, lowering the cost through peer sensitivity term $\nu_2 > 0$ as follows:

$$C_i^{\psi}(g_i, m_i) = (F_2 - \nu_2 K_a m_i) g_i. \tag{5}$$

I further parameterize the cost reduction with a binary exogenous neighborhood characteristic K_a, which identifies whether a neighborhood is amenable to such adoptions and the adoptions are on average financially beneficial. If broader neighborhood is potentially beneficial ($K_a = 1$), the search process of the focal household is aided by the peer adopters, reducing the cost C_i^{ψ} from F_2 to $F_2 - \nu_2 m_i$ (assumed to be positive). However, if broader neighborhood is not potentially beneficial ($K_a = 0$), the search process of the focal household stops since all peer adopters convey the true state of the neighborhood, that is, the adoption on average is not financially beneficial. In this case, the cost C_i^{ψ} becomes F_2, which is independent of the number of already-adopting peers.[10]

To sum up, the total cost of adopting green technologies for a household i is:

$$\text{Cost}_i(g_i, m_i) = C_i^P(g_i) + C_i^{\eta}(g_i, m_i) + C_i^{\psi}(g_i, m_i) = [C_i(\cdot) + F_1 - \nu_1 m_i + F_2 - \nu_2 K_a m_i] g_i. \tag{6}$$

A.3. Random Utility Error $\varepsilon_i(g_i)$

$\varepsilon_i(g_i)$ is a random utility term, independently and identically distributed across households. $\varepsilon_i(g_i)$ is privately observed by focal household i at the time of the decisions but is unobserved by the econometrician and other households. In line with the literature on discrete choice models, I assume that $\varepsilon_i(g_i)$ is Gumbel and type I extreme-value distributed (McFadden (1984), Brock and Durlauf (2001)).

[9] Such localized information includes (i) the broader neighborhood characteristics such as city (or zip code) microclimate, ground reflectivity, building zone, and utility tariffs (CEC (2008)), and contractor availability and installation cost (Dorsey and Wolfson (2024)); and (ii) home characteristics such as materials used in and geometry of walls, floors, attics, and roofs; HVAC and water heating systems; and internal air circulation and leakages.

[10] Note that in this formulation, information cost decreases more in $K_a = 1$ neighborhoods than in $K_a = 0$ neighborhoods. K_a could alternatively be modeled as an area-dependent economy of scale enjoyed by suppliers/contractors who pass on the benefits to households in terms of lower installation costs, and such scale is feasible in only certain neighborhoods ($K_a = 1$). The implications of the model remain unchanged under this alternative formulation and also when both the mechanisms coexist.

Incorporating the components from equations (2) and (6) into (1) gives:

$$u_i(g_i, m_i) = [\Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + (\nu_1 + \nu_2 K_a)\ m_i]\, g_i + \varepsilon_i(g_i). \tag{7}$$

B. Household Decision Rule and Equilibrium

Household i invests in residential green technologies when the utility from adoption outweighs that of non-adoption, i.e., $u_i(1) \geq u_i(0)$, leading to the decision rule:

$$u_i(1) - u_i(0) = \Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + (\nu_1 + \nu_2 K_a)m_i + \varepsilon_i(1) - \varepsilon_i(0) \geq 0. \tag{8}$$

Since $\varepsilon_i(1)$ and $\varepsilon_i(0)$ are independent and extreme-value distributed, the probability of adoption follows a standard logistic form (McFadden (1984)):

$$Pr(g_i = 1) = \frac{1}{1 + exp[-(\Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + (\nu_1 + \nu_2 K_a)m_i)]}. \tag{9}$$

We see that the probability of household i adopting green technologies is linked to the number of its green neighbor peers m_i through two sensitivity terms: ν_1 and $\nu_2 K_a$. First, the peers act as a source of information by lowering the cost of becoming aware about the green technologies ($\nu_1 m_i$). Second, conditional on being situated in areas where adopting the technologies is potentially beneficial ($K_a = 1$), peers also lower cost of acquiring localized neighborhood- and home-specific information ($\nu_2 K_a m_i$).[11]

The probability of adoption changes with respect to the number of already-adopting neighbor peers as follows:

$$\frac{\partial Pr(g_i = 1)}{\partial m_i} = \phi(z_i)(1 - \phi(z_i))(\nu_1 + \nu_2 K_a) > 0, \tag{10a}$$

$$\frac{\partial^2 Pr(g_i = 1)}{\partial m_i^2} = \phi(z_i)(1 - \phi(z_i))(1 - 2\phi(z_i))(\nu_1 + \nu_2 K_a), \tag{10b}$$

$$\text{where } \phi(x) = \frac{1}{1 + exp(-x)}; \text{ and } z_i = \Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + (\nu_1 + \nu_2 K_a)m_i$$

From equation (10a), the probability increases with the number of already-adopting neighbors m_i. However, the rate of increase in equation (10b) is positive when m_i is low ($\phi(z_i) < 0.5$) but negative when m_i is high ($\phi(z_i) > 0.5$), leading to a hump-shaped relation between the marginal probability of adoption and the number of already-adopting neighbors.

I next find the equilibrium adoption $\boldsymbol{m}^*$. Note that the expected decision $E(g_i)$ is equal to $Pr(g_i = 1)$, because g_i takes values $\{0, 1\}$. Assuming that households have

[11] Since $F_2 - \nu_2 m_i$ is assumed to be positive, ν_2 is capped, implying that financial benefits and peer effects can increase adoption only up to a certain limit. Beyond this threshold, additional incentives do not further impact the decision, preventing unbounded escalation.

rational expectations about neighbors' decisions, they correctly infer these decisions in expectation, i.e., $E_i(g_j) = E(g_j)$ for all households i and j, even though they do not fully observe others' decisions. By symmetry, at a self-consistent equilibrium, $E(g_i) = E(g_j)$ holds for all i and j, and this common individual expected value also equals the expected value of the average decision for any population subset (Brock and Durlauf (2001)). Therefore in equilibrium, $\boldsymbol{m}$ satisfies the following, and any fixed point solution $\boldsymbol{m}^*$ to this system of equations is an equilibrium:

$$\boldsymbol{m} = \frac{1}{1+exp[-(\Pi_i(\cdot)-C_i(\cdot)-F_1-F_2+(\nu_1+\nu_2K_a)\boldsymbol{W}\boldsymbol{m})]}. \tag{11}$$

$\boldsymbol{W}$ is an $I \times I$ weighting matrix, where row i specifies all neighbors of household i.

C. The Role of Green Preference in Adoption of Green Technologies

I now incorporate in the model households with green preference ($p_i = 1$). They adopt the green technologies also for pro-environmental motives and derive joy from taking actions related to sustainability or preventing global warming. I model such preference as an intrinsic taste parameter or identity of the households independent of the number of already-adopting neighbor peers. Therefore, the households with green preference ($p_i = 1$) receive additional utility δ from adopting green technologies as follows:[12]

$$\text{Utility: } u_i(g_i, m_i, p_i) = [\Pi_i(\cdot)+\delta p_i - C_i(\cdot)-F_1-F_2+(\nu_1+\nu_2K_a)m_i]g_i + \varepsilon_i(g_i). \tag{12}$$

$$\text{Probability: } Pr(g_i = 1) = \frac{1}{1+exp[-(\Pi_i(\cdot)+\delta p_i-C_i(\cdot)-F_1-F_2+(\nu_1+\nu_2K_a)m_i)]}. \tag{13}$$

This suggests that the green preference raise the probability of adoption but do not influence the peer effect, since the peer sensitivity term ($\nu_1+\nu_2K_a$) remains the same as the case with no green preferences in equation (9).

D. Social Optimum and Policy Implications under Peer Effects

Following Brock and Durlauf (2001), I model the social planner's objective $\mathcal{P}(\mathbf{g})$ as a utility function over green adoption decisions of the population, consisting of a deterministic and a random component $\mathcal{U}(\mathbf{g})$ and $\varepsilon(\mathbf{g})$ respectively:

$$\mathcal{P}(\mathbf{g}) = \mathcal{U}(\mathbf{g}) + \varepsilon(\mathbf{g}). \tag{14}$$

[12] This formulation of green preference is similar to that of prosocial preference in Bénabou and Tirole (2006) and altruism in Andreoni (1990). If the utility gain from green preferences were modeled alternatively to increase with the number of already-adopting neighbors, it would no longer be a pure preference but would rather represent a utility gain driven by social or reputational concern. For example, Bénabou and Tirole (2006) refer to the former as preference type or "identity" of the individual whereas to the latter as payoffs from reputational concerns.

$\varepsilon(\mathbf{g})$ is assumed to follow an independent extreme-value distribution across all 2^I possible configurations of $\mathbf{g}$. $\mathcal{U}(\mathbf{g})$ is the sum of individual deterministic utilities:

$$\mathcal{U}(\mathbf{g}) = \sum_i^I u_i(g_i, m_i). \tag{15}$$

By aggregating m_i's, the planner fully internalizes the total peer effect, including both (a) the positive effect of others' adoptions on i's decision; and (b) the positive effect of i's decision on yet-to-adopt neighbors. Under decentralized optimization in equation (8), individual households do not internalize (b). Its internalization doubles the adoption sensitivity to neighbor peers' decisions under planner's decision rule (Brock and Durlauf (2001), propositions 8 and 9):

$$\Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + 2(\nu_1 + \nu_2 K_a) m_i^S + \varepsilon_i(1) - \varepsilon_i(0) \geq 0. \tag{16}$$

The corresponding equilibrium satisfies:

$$\boldsymbol{m}^S = \frac{1}{1 + exp[-(\Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + 2(\nu_1 + \nu_2 K_a)\boldsymbol{W}\boldsymbol{m}^S)]}. \tag{17}$$

We see that aggregate adoption remains below the socially-optimum level without intervention by social planner. Social planner can achieve this optimum by offering households a subsidy S_i equal to the non-internalized portion of the peer effect:

$$S_i = (\nu_1 + \nu_2 K_a) m_i^S. \tag{18}$$

The slope of optimal subsidy with respect to peer effects can be obtained by total differentiation of equations (17) and (18) and rearranging as follows (see Internet Appendix A for derivation):

$$\frac{dS_i}{d\nu_1} = \frac{m_i^S}{1 - 2(\nu_1 + \nu_2 K_a) m_i^S (1 - m_i^S)}. \tag{19}$$

Note that m_i^S is a logistic function, hence $0 < m_i^S < 1$ and $0 < m_i^S(1 - m_i^S) < 0.25$. Therefore the denominator is positive so long as $\nu_1 + \nu_2 K_a < 2$. The empirical analogue of $\nu_1 + \nu_2 K_a$ is the coefficient β_1 on $\mathrm{N}_G(\leq 0.1 \text{ mi})$ in equation (22), which I estimate to be much smaller than two in Table II. Therefore the above expression is positive regardless of equilibrium adoptions m_i^S, implying that optimal subsidy increases with peer effects (under the current empirically estimated levels of peer effects).

E. Model Implications

The model generates the following testable implications:

IMPLICATION 1 (Peer Effects due to Information Transmission): (*i*) *The probability of a focal household to adopt the green technologies increases with the number of its neighbor peers who have already adopted the technologies—captured by* ν_1 *in equation* (9) (*the green peer effect*). (*ii*) *The relation between the marginal probability of adoption and the number of already-adopting neighbors is hump shaped* (*equations* (10a) *and* (10b)). (*iii*) *The mechanism underlying the green peer effect is information transmission, where neighbors reduce the cost of information.*

IMPLICATION 2 (Heterogeneity in Peer Effects due to Financial Benefits): *In areas characterized by* $K_a = 1$, *the decision sensitivity of the focal household* i *to its peers* $\boldsymbol{g}_{-i}$ (*through* m_i) *to adopt green technologies increases from* ν_1 *to* $(\nu_1 + \nu_2)$. *Such areas are those where adopting green technologies delivers additional financial benefits relative to other areas* (*equation* (9)).

IMPLICATION 3 (Green Adoption Decisions and Green Preferences): (*i*) *A focal household with green preference is more likely to adopt green technologies than a focal household without such preference.* (*ii*) *However, the decision sensitivity of focal households to peers' decisions* $(\nu_1 + \nu_2 K_a)$ *does not depend on their green preferences* (*equation* (13)).

IMPLICATION 4 (Policy Implications in Presence of Peer Effects): *When households optimize individually, the aggregate adoptions are inefficient and below the socially-optimum level* (*equations* (11) *and* (17)). *Under the current empirically estimated levels of peer effects, the inefficiencies can be reduced by allocating more subsidies to areas with stronger peer effects, that is, where* ν_1 *is higher or* $K_a = 1$ (*equation* (19)).

In the rest of the paper, I test these implications using a novel data on investments in residential green technologies by US households.

II. Institutional Background

A green certificate, often referred to as a "green building certificate" or "sustainability certification," is an official recognition that a building or property meets specific environmental and sustainability standards and is typically issued by recognized organizations. Such certifications aim to assess home's efficiency comprehensively and accurately by requiring on-site inspections to evaluate elements such as site, water, energy, indoor air quality, construction materials, operation, and maintenance (Department of Energy (2010)). For example, the Home Energy Rating System (HERS)—the most popular certification program in the US—evaluates various aspects of a home's energy efficiency, including insulation levels, air leakage, HVAC system performance, and overall energy consumption.[13] As a result, meeting these standards implies a significant investment in upgrades or remodeling of the home, making these certifications a valid proxy for residential green investment. In Section VI.A, I provide evidence corroborating that the certifications represent real investments in homes. Figure 1 provides sample green certification reports of HERS and HES programs, along with a word cloud of the contents of these reports.

[Insert Figure 1 About Here]

This paper focuses on 15 residential green certification programs across the US, six of which are national and the rest are regional. Table IA.I of Internet Appendix summarizes the programs by geographical coverage, attributes evaluated, and green contractor requirements. Their focus varies widely: some, like HERS and the Home Energy Score (HES), assess only home energy efficiency, whereas others, such as Earth Advantage® Certifications, take a more comprehensive approach by also evaluating environmental performance and building materials.

The annual number of certifications has grown significantly starting from 2010, with about 1.5 million single-family properties certified as of November 2022 (Panel A of Figure IA.1 in Internet Appendix). Panel B shows the spatial distribution of the proportion of green-certified single-family properties across counties in 2022. We see that counties in metropolitan areas exhibit a higher concentration of green-certified homes. Panel A of Figure IA.2 in Internet Appendix shows the distribution of certifications across the 15 programs, with HERS accounting for about 94% of the certified homes. Panel B shows the relation between the estimated utility savings and HERS scores.

The certifications provide guided information for residential investments and are obtained typically following one of the two pathways: through a green contractor or homeowner directed. In the first, homeowners hire a green contractor affiliated with a certification organization. The contractor follows the set guidelines and coordinates with an affiliated rater to certify the property after completion of the renovation. In the second, homeowners themselves decide the renovations by specifying certification requirements and hire a contractor to complete the renovations. Afterward, they independently hire a rater to assess and certify the home. In summary, the certification programs provide information that guides investments in residential green technologies. Figure IA.4 of Internet Appendix provides anecdotal examples of the processes.

[13] Figure IA.3 of Internet Appendix provides examples of green certification technical standards. More technical details of HERS are available in CEC (2008).

III. Data, Sample Construction, and Summary Statistics

A. Data

I use two main datasets: property, deed and mortgage data compiled by the Warren Group from county records offices and green certification data from the Green Building Registry (GBR).[14] The property data cover more than 155 million properties in the US and contain information on their geolocations, addresses, and property characteristics such as year built, living area, number of bedrooms, exterior materials, fuel type, heating system etc. The deed and mortgage data contain 104 million records of housing and mortgage transactions from 2018 to 2022. They include information on sale price, date and type; names of buyers, sellers and lenders; and mortgage type, amount, term, interest rate etc. The GBR is the largest green certification database of residential and commercial properties in the US containing certification records for over two million properties as of 2022. From these records, I collected information on certification program, type, date, score (or rating), and the reports, as well as property geolocations and addresses.

I also draw on several other datasets. I use building permit data from Builty to measure real investments in residential properties,[15] the Home Mortgage Disclosure Act (HMDA) data to measure mortgage patterns, and local house price index from the Federal Housing Finance Agency. Furthermore, I use the database of state incentives for renewables & efficiency (DSIRE) to measure regulatory green incentives. I proxy for household green preferences using opinion data from the Yale climate opinion maps (Howe et al. (2015)) and electric vehicle registration data from the Atlas EV hub. I utilize socioeconomic and demographic data from the US Census and statistics of income (SOI) from the Internal Revenue Service (IRS).

B. What is a Green-Certified Home?

I define a home as green when its assessed environmental performance under a given green certification program exceeds that of an average US home. Since the programs follow different methodologies to assess their performance of homes, I examine each of the 15 certification programs and their scores (or rating categories) to identify the

[14] The Warren Group: https://www.thewarrengroup.com/our-data/. The Green Building Registry: https://us.greenbuildingregistry.com/.

[15] This data was made available by Builty Inc. (https://www.builtydata.com/) via the Dewey Data platform. (https://www.deweydata.io/)

program-specific threshold for the performance of an average US home.[16] Using these thresholds, I create an indicator—Green—to take the value of one when the score (or rating category) exceeds the respective threshold. This definition measures the green certification status of homes uniformly across different programs. Table IA.I of Internet Appendix provides thresholds for the scores (or rating categories) under each program. I define a property to be green certified when it crosses the threshold under any of the programs for the first time.

C. Sample Construction

I begin by cleaning the property transaction data broadly following Bayer, Mangum, and Roberts (2021). I retain all properties owned by individuals (as opposed to non-person entities). I then exclude: (i) the properties that were subdivided and resold; (ii) transactions less than $1 or those marked non-arms-length; (iii) multiple same-day transactions; and (iv) potential data inconsistencies, such as a transaction occurring earlier than year built. This yields a sample of about 73.8 million single-family properties and associated ownership tenures. I then remove properties in counties that have no green homes over the sample period from 2018 to 2022, given that this paper aims to evaluate peer effects of green neighbors. Using the cluster-computing infrastructure of the University of Texas at Dallas, I create a spatial dataset identifying the single-family properties located within 0.1, 0.3, and 0.5 miles of each of these properties, a highly computationally demanding task. This dataset is structured as pairs consisting of focal properties and each of the properties located within 0.5 miles. I then merge the first-ever green certification status of the properties using geolocations and addresses. In the resulting dataset, I count for each quarter from 2018 till 2022 and for each focal property, the number of neighboring properties (owned by individuals or otherwise) that became green for the first time within 0.1, 0.3 and 0.5 miles over the previous four quarters (inclusive of the current quarter). These counts represent the green exposure of focal households within 0.1, 0.3 and 0.5 miles. I stack these quarterly counts for each focal household to create a focal-household×quarter level panel. From this panel, I remove a focal household a quarter after it becomes green, if it does so over the sample period. This yields the baseline estimation panel of 1,037,652,080 observations from 2018 till 2022 recording certification status and green

[16] Consider for example, the scores under the Home Energy Score (HES) Program. A score of 5 indicates energy efficiency equivalent to that of an average US home, 10 indicates the top ten percentile, and 1 indicates the bottom 15 percentile (Department of Energy (2024)). I therefore assign properties rated under the HES program to be green certified (Green= 1) if their scores are higher than 5.

exposures for focal households owning 56,546,251 unique single-family properties across 1,632 counties.

D. Summary Statistics

Table I reports the summary statistics for the main variables. The mean of the variable Green (=10,000) in the property×year-quarter panel is 0.004 percent, which is the average probability of a household to make green investments in a given quarter. The mean of the variable Green (=10,000) in the property panel is 0.0747 percent, implying that 0.0747 percent of the households become green at a quarterly hazard rate of 0.004 percent. The average household has 0.09, 0.37 and 0.62 neighbors within a 0.1-, 0.3- and 0.5-mile ring respectively who became green within the last four quarters. A typical single-family property in the sample was built in 1974 and has 2.49 bedrooms and a living area of 1855.41 square feet. An average county has 3.68 green financial incentives offered by state and county governments, and has 53.87% of adults somewhat or very worried about global warming. The average housing density in a census tract is 2.06 residential properties per acre, and the average annual house price growth in a census tract is 4.52%. The mean adjusted gross income per capita in a zip code is $33,960.

[Insert Table I About Here]

IV. Empirical Research Design

Attributing causal interpretation to the neighborhood peer effect faces the two key endogeneity issues. First, households are not randomly assigned to specific neighborhoods, because they may sort into neighborhoods due to factors such as preferences, income, and social networks. Second, neighborhood-level shocks may cause households to simultaneously make similar decisions. I address these issues by employing a nearest-neighbor research design (Bayer, Mangum, and Roberts (2021), McCartney and Shah (2022), Towe and Lawley (2013), McCartney, Orellana-Li, and Zhang (2024)). It estimates the effect of decisions by hyper-local neighbors located within 0.1 miles, while controlling for the same decisions made by neighbors located slightly away within 0.3 and 0.5 miles. I illustrate the design in Figure 2. Panels A and B respectively show a green and non-green focal property and their green neighbors.

[Insert Figure 2 About Here]

This research design relies on two crucial assumptions. First, the assignment of the within-0.1-mile neighbors within the slightly broader neighborhoods of 0.3 or 0.5 miles is quasi-random, an assumption that single-family housing market likely satisfies for two reasons. Firstly, socioeconomic characteristics including race, income, and price growth tend to be remarkably similar within small areas, such as 0.5 miles (Bayer, Ross, and Topa (2008), Bayer, Mangum, and Roberts (2021), Towe and Lawley (2013), McCartney and Shah (2022), McCartney, Orellana-Li, and Zhang (2024)), indicating an absence of household sorting within these small areas. Furthermore, I demonstrate later that property characteristics, which are key determinants of green investments, are also similar within 0.5 miles. Secondly, limited availability of for-sale properties arising from the thinness of single-family housing market within such small areas diminishes households' ability to freely select a specific property.

The second assumption concerns information transmission among neighbors. It assumes that social interactions are more prevalent within 0.1-mile neighborhoods than in broader neighborhoods, since households tend to interact more with their next-door neighbors compared to those living slightly further away. This is an implicit condition for finding a non-zero effect, because if neighborhood interactions were not stronger at hyper-local geographies, the estimated effect would be zero.

A. Property Characteristics Similarity

I use the proportional difference in property characteristics to assess whether they are similar within 0.5-mile neighborhoods. For a focal property i, the proportional difference in characteristic c with all its neighboring properties j located within a ring (donut) of d miles is:

$$\text{Proportional Diff}_{cid} = \frac{c_i - Avg(c_j)_{j \in [d-0.1:d]}}{c_i}, \; d \in \{0.1, 0.2, \ldots 0.5\}. \tag{20}$$

The average of this difference across all properties i is plotted in Panel A of Figure 3 for four characteristics: year built, living area (in square feet), number of bedrooms, and building condition (measured on an ordinal scale from 1 to 6, 1 being excellent and 6 being unsound). We see that there are no jumps in the proportional difference for any of the four characteristics as the distance from focal property increases, indicating a high similarity among these neighboring properties.

[Insert Figure 3 About Here]

To understand the spatial difference in green exposure experienced by green (G) and non-green focal properties (NG), I calculate the proportional difference as follows:

$$\text{Proportional Diff}_{\text{Green Exposure}, \, d} = \frac{Avg\left(\text{Exposure}_{id}\right)_{i \in G} - Avg\left(\text{Exposure}_{id}\right)_{i \in NG}}{Avg\left(\text{Exposure}_{id}\right)_{i \in NG}}. \tag{21}$$

Here *Avg* is the average across i calculated separately within group G and NG; and $d \in \{0.1, 0.2, \ldots 0.5\}$.[17] Panel B of Figure 3 plots this proportional difference in green exposure with distance. We see that while it remains stable in the broader neighborhoods of 0.2 to 0.5 miles, it rises sharply in the immediate neighborhood of 0.1 miles. This suggests that households who make residential green investments experience many more green neighbors in their close neighborhoods than those who did not invest.

We see from these two plots that while property characteristics largely remain stable over immediate neighborhood, green exposure is significantly higher for green homes than non-green homes, implying that the property characteristics alone do not drive the green investments.

B. Regression Specification

Similar to Bayer, Mangum, and Roberts (2021), I use the following regression specification for the nearest-neighbor research design:

$$Green_{it} = \alpha + \beta_1 \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \times N_G(\leq 0.5 \text{ mi}) + \theta_t + \theta_j + \epsilon_{it}, \quad (22)$$

where $Green_{it}$ is an indicator that takes on a value of 10,000 if household i obtains the first-ever green certificate for his or her property in quarter t. The key variable of interest is the exposure a focal household i receives from immediate green neighbors within 0.1 miles, denoted as $\mathrm{N}_G(\leq 0.1 \text{ mi})$. Recall that it is equal to the number of neighbors within 0.1 miles who obtained green certificates within quarters $t-3:t$. The other two exposures—$\mathrm{N}_G(\leq d \text{ mi})$, where $d \in \{0.3, 0.5\}$—control for effects of similar activities occurring at wider distance rings of $d = 0.3$ and 0.5 miles. Since the three exposures are measured cumulatively, that is, the exposure in outer rings are inclusive of the inner ring, the coefficient β_1 measures the additional effect of the exposure occurring within the closest ring beyond the effect of exposures occurring in 0 to 0.5 miles. The specification includes fixed effects for spatial and temporal characteristics, θ_t and θ_j. The specific choices for these fixed effects vary across estimations and are discussed along with the respective results in Section V.

[17] The green group G consists of all properties j which received green certification in year-quarter q. I construct the non-green group NG by randomly drawing (with replacement), for each green property j in year-quarter q, 50 properties that were non-green in that quarter. Indexing the combined properties in the two groups with i, I define green exposure $Exposure_{id}$ of a property i over a ring of d miles as the total number of neighboring properties within the d-mile ring that became green from $(q-3)$ to q. Here, q is the year-quarter a property i was assigned to its respective G or NG group, and a ring of d miles refers to a donut of $(d-0.1)$ to d miles, where $d \in \{0.1, 0.2, \ldots 0.5\}$.

Additionally, to account for local characteristics, I add *Property controls*$_{it}$ and *Neighborhood controls*$_{it}$ to equation (22) as follows:

$$Green_{it} = \alpha + \beta_1 \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \times N_G(\leq 0.3 \text{ mi}) + \beta_3 \times N_G(\leq 0.5 \text{ mi}) \\ + \delta_1 \text{Property controls}_{it} + \delta_2 \text{Neighborhood controls}_{it} + \theta_t + \theta_j + \epsilon_{it}, \qquad (23)$$

where property controls include property age, living area, # bedrooms, exterior materials, heat type and roof materials. Neighborhood controls include residential housing density and annual housing price growth at census tract level, adjusted gross income per person at zip code level, number of regulatory green incentive programs and climate change concern at county level, and the proportion of green homes within a ring d = 0.1, 0.3 and 0.5 miles. These variables are defined in Table I.

V. Results

A. Baseline Results

I begin the empirical analysis with a preliminary graphical analysis of variations in the probability of focal households investing in residential green technologies to certify their homes green (henceforth, green investments) with the number of green neighbors located at different distances who became green in the last four quarters.[18] Moving from left to right in Panel C of Figure 3, we see that the probability of green investments rises with the number of green neighbors located within a given distance. More importantly, the steeper slope of 0.1-mile line indicates that the effect of green neighbors is stronger when they are located spatially closer to the focal households (within 0.1 miles) than slightly farther away (in rings of 0.2, 0.3, 0.4, and 0.5 miles). These patterns suggest that spatially closer green neighbors have stronger influence.

To quantify the effect of green neighbors, I first use a version of the specification in equation (22) where I exclude the outer ring neighbors. Column (1) of Table II reports the result. The coefficient on $N_G(\leq 0.1 \text{ mi})$, 0.69, represents the incremental effect of one additional green neighbor within 0.1 miles. Equivalently, one additional within-0.1-mile green neighbor raises the likelihood of a focal household to make green

[18] Green neighbors located within d miles are defined as those who have become green in the past year, where d is [0, 0.1], (0.1, 0.2], (0.2, 0.3], (0.3, 0.4], and (0.4, 0.5]. The number of green neighbors is grouped in seven bins consisting of 0, 1, [2, 5], [6, 10], [11, 15], [16, 20], and greater than 20 neighbors. The average probability is calculated in quarter q for each bin and each distance ring d as the ratio of the number of properties that turn green for the first time in quarter q to the total number of properties (in the respective bin and ring) that did not become green until quarter $q-1$. The mean of these average probabilities across quarters is plotted in percentages on the y-axis. The count of neighbors over a given distance ring is independent of the count over other rings.

investments in a quarter by $\beta/\alpha = 0.692/0.318 = 2.18$ times relative to that of unexposed focal households (who have zero green neighbors within 0.1 miles). This value is reported in the table as *Marginal Effect to Hazard Ratio*.

[Insert Table II About Here]

I now implement the nearest-neighbor research design following equation (22), which incorporates green neighbors within 0.3 and 0.5 miles. The estimate in column (2) suggests that one additional within-0.1-mile green neighbor raises the likelihood of a focal household to make green investments in a quarter by 1.58 (= 0.329/0.208) times *in excess of* the exposure from one additional green neighbor within 0.3 and 0.5 miles.[19] The magnitude is sizable compared to the peer effects documented in other similar settings, namely, 8% for housing investment decisions (Bayer, Mangum, and Roberts (2021)) and 3.3% for refinancing decisions (McCartney and Shah (2022)). Column (3) incorporates year-quarter and zip code fixed effects; and column (4), zip code×year-quarter fixed effects. These specifications consistently yield similar coefficients and hazard ratios, highlighting the robustness of the results. These findings empirically support IMPLICATION 1 (i) of the model.

I repeat these regressions following equation (23) by adding controls for property and neighborhood characteristics and report the results in Table IA.II of Internet Appendix. These estimates remain qualitatively and quantitatively similar, reaffirming the evidence of the green peer effect.

I now gauge the validity of the key assumption of the nearest-neighbor research design, that is, neighbors within 0.1-mile area of a focal household are quasi-randomly assigned. I rely on the idea that the ability of households to self-select into preferred neighborhoods is relatively low in areas where housing supply is constrained. Therefore, the assumption is more likely to hold in such neighborhoods. To do so, I re-estimate the baseline results separately in areas below and above the median value of Wharton Residential Land Use Regulatory Index (WRLURI) (Gyourko, Saiz, and Summers (2008), Gyourko, Hartley, and Krimmel (2021)). The estimates in Table IA.III of Internet Appendix consistently suggest that the green peer effect is statistically significant in supply-constrained areas as well, suggesting that household sorting alone cannot explain the effect and thus supporting the validity of the assumption.

IMPLICATION 1 (ii) suggests that the relation between the green peer effect and the number of already-adopting neighbors is hump shaped. To test this relation, I estimate

[19] The regression coefficients flexibly allow estimation of alternative hazard ratios. For example, one additional green neighbor located at 0.4 miles increases the likelihood by 0.36 times ($\beta_3/\alpha = 0.075/0.208$).

equation (22) separately in subsamples consisting of observations in the deciles of the fraction of within-0.5-mile homes that are green. The coefficient β_1 on $N_G(\leq 0.1 \text{ mi})$ is plotted in Panel A and the associated marginal hazard ratio in Panel B of Figure 4. The plots align with the hump-shaped relation, as predicted. Intuitively, this implies that the peer effect increases sharply with the number of adoptions at lower levels of adoptions. As more and more neighbors adopt, the information (about the green technologies) becomes common knowledge, and the influence of neighbor peers in lowering the cost of information for focal households diminishes. The effect therefore tapers as the adoptions increase.

[Insert Figure 4 About Here]

I next undertake a series of additional tests to rule out alternative explanations and assess the robustness of the baseline results. I first examine whether green certifications reflect real investments in homes by using building permits and IRS residential energy tax credits, both of which indicate verified investments in homes. In Section VI.A, I describe these tests in detail and find that green certificates indeed reflect real investments. Furthermore, I confirm that the peer effect occurs in real investments by re-estimating the baseline model for the subsample of green homes that have a record of building permit issued within one year prior to the certification date. The results in Table IA.IV of Internet Appendix show that the green peer effect exists in this subsample. This rules out the concern that the green peer effect is observed only in certifications, not in real investments.

Second, to show that the green peer effect is reflected in household investments in green technologies, not in general home improvement, I re-estimate the baseline model in an alternative sample consisting of only the home improvements which are unrelated to green technologies. In Section VI.B, I show that there is no peer effect in such non-green home improvements.

Third, I address the concern that the green peer effect simply reflects a spatial clustering of homes constructed by the same builders who are likely to include the same features in those homes. I re-estimate the baseline model in the subsample of green homes which received certification more than two years after their first recorded sale and had been issued a building permit within this time period, ensuring that it is the household, not the builder, who initiated the green certification of the home and made verified investments. In Section VI.C, I show that the estimate of the green peer effect remains similar in this subsample, indicating that builder decisions alone cannot explain the effect.

Fourth, I emphasize the role of information in driving the peer effect (as hypothesized in the model) by estimating it in a placebo sample where information from green neighbor peers is unlikely to be valuable. This placebo sample consists of focal households whose green exposures arise exclusively from neighbors for whom the green certification processes revealed that their homes' efficiency was lower than that of an average home (inefficient green certificates). In such cases, the information role of neighbors is diminished, and the peer effect should be negligible, if any. Indeed, I do not find a statistically significant peer effect in this sample, as shown in Table IA.V of Internet Appendix.

The analyses in the rest of the paper are based on the specification in column (3) of Table II. This specification does not include controls. This choice is motivated by the benefits and computational burden of including the granular fixed effects in this large panel data, the stable nature of the coefficients across different fixed effects specifications, and the reduction in the number of observations caused by the inclusion of controls for property and neighborhood characteristics.

B. Mechanism: Information Transmission

The baseline analysis in the previous section shows the peer effects of immediate green neighbors but does not identify the underlying mechanism. In this section, I investigate the information transmission mechanism, as postulated in IMPLICATION 1 (iii) of the model. I first analyze green investment decisions of multi-property owners (MPOs) for their secondary properties, followed by peer commonalities in green decisions, and heterogeneity in peer effects by the strength of local community interactions.

B.1. Green Investment Decisions of Multi-Property Owners

The increased probability of green investment among close neighbors could arise not only due to information flow from neighbors, but also due to any neighborhood-specific characteristics, such as contractor availability or geo-spatial features. Such features may not necessarily be observable to researchers, confounding the estimates of peer effect. To mitigate this concern and to isolate the role of information flow, I focus on decisions of focal MPOs to make green investments in their secondary properties located faraway from their primary homes (greater than 20 miles). The idea is that while MPOs receive informational exposure from the green neighbors located around their primary residence, their secondary property remains uninfluenced from primary neighborhood-specific characteristics and shocks, except for the informational exposure. This exposure is more relevant when there is similarity between the secondary property and the primary neighbors of a focal MPO. Therefore, under information transmission mechanism, the green exposure in the primary neighborhood would raise the likelihood of green investments in the secondary properties of MPOs when the similarity is high.[20]

[Insert Table III About Here]

To test the above predictions, I estimate equation (22) in a sample of all secondary properties of MPOs while including green exposures arising from both primary ($N_G(\leq d\ mi)_{Primary\ Home}$) and secondary neighbors ($N_G(\leq d\ mi)_{Secondary\ Property}$) within d = 0.1, 0.3, and 0.5 miles. Table III reports the results. We see that within-0.1-mile green exposure from primary neighbors is statistically significant in columns (1) and (2) where the similarity is high (top quartile) and not statistically significant in columns (3) and (4) where the similarity is low (bottom quartile).[21] These results support information transmission mechanism and contradict the explanation that neighborhood characteristics alone drive the peer effect.

B.2. Peer Commonalities in Green Certificates and Lenders

I further test the information transmission mechanism by examining the commonalities in the green investment decisions of neighbor peers that help shed light on the specific information types being transmitted, such as green technology specifications. If focal households receive and act on information about green decisions from neighbors, their choices are more likely to be similar to those of their spatially closer neighbors. I exploit the richness of the dataset to test for peer commonality in the choice of green certification program, text description of the undertaken green investments, and choice

[20] The similarity is calculated as follows. I first find Gower's distance (a similarity measure) between MPO's secondary property and each of the neighboring properties located within 0.1 miles of MPO's primary home. I then calculate the similarity as the mean across these distances for a given secondary property. The Gower's distance is computed based on property age, living area, exterior materials, heat type and roof materials.

[21] The smaller effect of primary relative to secondary exposure is consistent with the role of general and specific information in the model. In this case, primary exposure aids MPOs with general information about green technologies, whereas secondary exposure aids them with specific, localized information regarding the secondary property (see Footnote 9), equivalent to lowering C_i^{η} and C_i^{ψ} respectively in the model. Similarly, Chinco and Mayer (2016) find that MPOs' (out-of-town second-house buyers') decisions are influenced by factors from both their residence and the location of their purchases.

of lender for debt-financed green investment using the following specification:

$$y_{injzt} = \alpha + \beta \times \mathbb{1}(\text{Dist.} \leq 0.1 \text{ mi})_{injzt} + \theta_n + \theta_{zt} + \epsilon_{injzt}. \quad (24)$$

y_{injzt} represents the similarity in the decision choices of household i during tenure n of a property and a green neighbor j located within 0.5 miles. z represents zip code of focal household's property, and t represents year-quarter of focal household's decision. The indicator $\mathbb{1}(\text{Dist.} \leq 0.1 \text{ mi})$ is one when the distance between focal household and neighbor is within 0.1 miles. The coefficient of interest is β. Ihe specification includes fixed effects for focal household's tenure θ_n and zip code-quarter θ_{zt}.

To test for commonality in choice of certification program, I select all green focal households and their within-0.5-mile green neighbors and create a pair dataset at "focal×neighbor" certificate level. I then define the outcome $\mathbb{1}(\text{Same Cert.})$ to take the value of one when the certificates are the same for the focal-neighbor pair and regress it on an indicator for within-0.1-mile neighbors. Column (1) of Table IV shows the result for all certificates, and column (2) shows the result after excluding HERS, the most common program. The respective coefficients indicate that focal households are 0.5 and 1.1 percentage points more likely to choose the same certification as their within-0.1-mile neighbor peers relative to slightly farther neighbors.

[Insert Table IV About Here]

Next I examine commonality among peers in their green investments using text similarity of the green certificate and of the description of the building permits obtained by them within one year prior to the green certification. Text similarity of these descriptions allows me to directly examine the type and specification of the green investments undertaken among neighboring households. I compute textual cosine similarity of the descriptions of green certificates and building permits in the above pair dataset. The steps for text analysis are provided in Section B of Internet Appendix. The results of regressing these similarity measures following the earlier specification are shown in columns (3) and (4). We see that green investment specifications of focal households are more similar to those of within-0.1-mile neighbors.

For the cases where households finance green investments using mortgages, neighbor peers could aid focal households with information regarding lender choice. They may lower the cost of researching lenders by providing information about availability of cheaper credit, approval probability, tailored schemes and rebates targeted towards residential green investments etc. To shed light on this type of information flow, I examine commonality among peers in their lender choice. I begin by selecting focal households and their within-0.5-mile neighbors who each took a mortgage within 90 days before respective green certification date, in a bid to ensure that their green investment was mortgage-financed. Furthermore, I keep only those neighbors whose mortgage date is within one year prior to that of the focal household, in order to ensure that the information regarding the lenders and financing is timely. I then create a "focal×neighbor" mortgage panel and define the indicator $\mathbb{1}$(Same Lender) to take the value of one when the pair borrows from the same lender.

The result of regressing this indicator on the indicator for within-0.1-mile neighbors in column (5) shows that focal households are 9.4 percent more likely to use the same lender as their 0.1-mile neighbors to finance green investments. Moreover, to ensure that the commonality in lender choice is not driven by presence of a few dominant lenders, I re-estimate the effect excluding the top three lenders (in terms of the aggregate loan amount in mortgage applications received in a county-year). The results in column (6) remain essentially the same. Similar peer commonality in lender choice has been shown in refinancing (Maturana and Nickerson (2019)) and property investing (Bayer, Mangum, and Roberts (2021)).

Taken together, the commonalities among green peers regarding certification program, investment specification and lender choice are consistent with the information transmission mechanism.

B.3. Heterogeneous Peer Effects: The Role of Local Community Interactions

If the information transmission is the key mechanism underlying the green-peer effect, the effect would be more pronounced in areas where local community interactions are stronger. I thus conduct a series of tests examining heterogeneity in peer effects by the strength of local community interactions $\mathbb{X}$. I utilize three measures based on social ties: social connectedness index and support ratio in a zip code and social capital, SK 2014, in a county.[22] Additionally, I utilize a housing market based measure of community interactions defined as the percentage of properties in a zip code owned for investment purposes (McCartney and Shah (2022)). Since such investment properties are not occupied by owners, who plan and decide residential investments, the ability of

[22] The social connectedness index measures the strength of connectedness using Facebook friendship ties, and support ratio is the proportion of within-zip code friendships where the pair of friends share a third mutual friend within the same zip code (Bailey et al. (2018), Chetty et al. (2022)). Social capital (SK 2014) is derived from principal component analysis using the number of social organizations, voter turnout, census response rates, and the number of non-profit organizations, excluding those with an international approach (Rupasingha, Goetz, and Freshwater (2006), with updates).

focal households in areas with high fraction of investment properties to receive relevant information from neighbor peers is hindered even though their neighboring properties are green certified. I use the following specification for the heterogeneity tests:

$$\begin{aligned} Green_{it} = \alpha + \beta_1 \mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.1 \text{ mi}) + \beta_2 \mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.3 \text{ mi}) \\ + \beta_3 \mathbb{1}(\text{High } \mathbb{X}) \times N_G(\leq 0.5 \text{ mi}) + \beta_4 N_G(\leq 0.1 \text{ mi}) \\ + \beta_5 N_G(\leq 0.3 \text{ mi}) + \beta_6 N_G(\leq 0.5 \text{ mi}) + \delta \mathbb{1}(\text{High } \mathbb{X}) + \theta_t + \theta_j + \epsilon_{it}. \end{aligned} \tag{25}$$

Here the indicator $\mathbb{1}(\text{High } \mathbb{X})$ is equal to one for above-median levels of the measure $\mathbb{X}$ of community interactions. The coefficient of interest is β_1.

Table V reports the results. The positive and statistically significant β_1 in columns (1) through (3) indicates that the green-peer effect is stronger in areas with stronger social ties. The negative and statistically significant β_1 in column (4) suggests that the green-peer effect is weaker in areas where the ability of focal households to receive relevant information from neighbors is limited. These findings are in line with the literature showing that interactions within a community are associated with transmission of valuable information (Beaman (2012), Burchardi and Hassan (2013)).

[Insert Table V About Here]

In summary, all the findings in this section consistently align with the information transmission mechanism postulated in IMPLICATION 1 (iii) of the model.

C. Financial Benefits of Green Homes and the Green-Peer Effect

I now proceed to examine IMPLICATION 2 of the model concerning heterogeneity in green peer effects by potential financial benefits of green homes. It predicts that in areas where green investment is associated with higher financial benefits, the green-peer effects would be stronger. I therefore examine whether the green-peer effect is stronger in areas where green homes fetch relatively higher financial benefits. Relatedly, I also test whether the green-exposed households who make the green investment realize higher financial returns relative to similarly exposed households who did not invest.

C.1. Heterogeneous Peer Effects: The Role of Potential Financial Benefits

I draw on three measures of potential financial benefits of green homes to understand how they shape the strength of peer effect. I estimate the benefits in three ways—house prices, electricity savings, and regulatory monetary incentives.

Regarding the first measure, house prices, I identify the counties where green homes fetch higher prices than observationally equivalent non-green homes by separately estimating hedonic regression of house prices on property characteristics for each county and year as follows:[23]

$$ln(Price)_{it} = \alpha + \beta\ Green_{it} + \gamma\ Control_{it} + \theta_z + \epsilon_{it}. \quad (26)$$

The coefficient of interest β measures the difference in average house price of green homes relative to non-green homes. Control variables include property age, living area, # bedrooms, exterior materials, heat type, roof materials, an indicator of mortgage-financed purchase, mortgage term, and mortgage interest rate. I also include zip code fixed effects θ_z to account for zip code-level unobserved time-invariant characteristics. The sample includes the green homes that were sold and purchased by individual sellers and buyers within four years following homes' green certification. Panel A of Figure IA.5 in Internet Appendix shows the number of years (from 2018 to 2022) for which the coefficient β is statistically positive at the 10% level or below for a given county. It shows a substantial regional variation in financial benefits of green homes, in line with Dauwalter and Harris (2023). Panel B shows that 16% of county-year observations exhibit a statistically significant positive green premium, which I identify by the indicator $\mathbb{1}(\mathbb{B}\text{ exists})$ for use in the subsequent heterogeneity regression.

Regarding the second measure, potential electricity savings, I classify the utility service territories that have above-median (calculated yearly) marginal retail electricity prices as having high financial benefit by the indicator $\mathbb{1}(\mathbb{B}\text{ exists})$.[24] This is because the higher marginal prices raise attractiveness of green homes relative to non-green. Panel B of Figure IA.2 in Internet Appendix confirms that utility savings are positively associated with the energy efficiency score of green-certified homes.

Regarding the third measure, regulatory monetary incentives for green homes, I identify the counties with above-median (calculated quarterly) number of county- and state-level green incentives as having high financial benefit by the indicator $\mathbb{1}(\mathbb{B}\text{ exists})$.

[23] While this hedonic regression approach does not measure whether the net present value (NPV) of the green investment is positive, it identifies the housing submarkets where the prices of green homes are higher than non-green homes and is widely used in the literature on housing and real estate (Kahn and Kok (2014), Aydin, Brounen, and Kok (2020), Pigman et al. (2022), Muehlenbachs, Spiller, and Timmins (2015), Keiser and Shapiro (2019), Avenancio-León and Howard (2022)). Admittedly, while calculating the NPV of the green investments is infeasible, I show in Section VI.D that green homes enjoy a price premium and lower price volatility, and green home improvements deliver higher returns than non-green home improvements.

[24] I follow Borenstein and Bushnell (2022) to calculate the marginal retail electricity prices and use data from the Energy Information Administration's Form EIA-861 survey (EIA (various years)) and the National Renewable Energy Laboratory's Utility Rate Database (URDB) (National Renewable Energy Laboratory (various years)). I exclude Texas because the Texas Public Utilities Commission stopped updating the report cards on retail competition and summary of market share data since September 2017.

The incentive data are from the financial incentive category of the DSIRE database. The incentives include net metering benefits and fee reduction for solar panel installation.

[Insert Table VI About Here]

Having identified the area-time combinations where green homes fetch higher potential financial benefits, I examine whether the green-peer effect is stronger in these areas using specification in equation (25), where I replace the indicator $\mathbb{1}(\text{High } \mathbb{X})$ with the indicator for the three potential benefits, $\mathbb{1}(\mathbb{B} \text{ exists})$. Table VI reports the regression results. The coefficients on $\mathbb{1}(\mathbb{B} \text{ exists}) \times N_G(\leq 0.1\, mi)$ suggest that the green-peer effect is more pronounced in the areas where the potential benefits are stronger, highlighting that financial motives shape the peer effect in residential green investments. These results are consistent with IMPLICATION 2 of the model.

C.2. Do Peer-induced Green Investments Deliver Higher Housing Returns?

I now examine whether the green-exposed households who make the green investment realize higher financial returns relative to similarly exposed households who did not invest. To do this, I create a sample of green-exposed households who green certified their homes and similarly-green-exposed households who did not certify their homes.[25] I then define an indicator $\mathbb{1}(Green)_i$ to take the value of one for the certifying households and zero for the non-certifying and estimate the following regression:

$$y_i = \alpha + \beta\, \mathbb{1}(Green)_i + \theta_{\text{buy year}} + \theta_{\text{sell year}} + \theta_{\text{green year}} + \epsilon_i. \tag{27}$$

The coefficient of interest β estimates the difference in housing return realized by households who made residential green investments during their ownership relative to those who did not. The regression includes fixed effects for buy, sell and green certification year. The outcome variable is return on housing transactions measured as the annualized rate of return and sell residual.[26] Table VII reports the results. The

[25] I begin with the households who bought and sold their properties from 2018 to 2022 and create two subsamples: those who certified their homes (compliers C) and those who did not certify their homes over this period (non-compliers NC). C consists of all households j who green certified their homes in a given year-quarter q during their ownership of the properties and had at least one green neighbor within 0.1 miles in the past year. NC is constructed by randomly drawing (with replacement) 50 never-certifying households in year-quarter q—who also had at least one green neighbor within 0.1 miles in the past year—for every given certifying household j of year-quarter q from complier subsample C.

[26] The sell residuals are obtained from the following repeat-sale regression estimated separately for each county: $\ln(\text{Price})_{int} = a_{in} + \delta_t + \theta_n + \mathbb{1}(\text{Non-Person Buyer})_{int} + \mathbb{1}(\text{Non-Person Seller})_{int} + \epsilon_{int}$. Here the outcome variable is the natural logarithm of transaction price occurring in year-quarter t of property i's n−th transaction. a_{in}, δ_t and θ_n respectively represent fixed effects for property, year-quarter and transaction sequence (five or more transactions are grouped together).

estimates in columns (1) and (2) suggest that the green-exposed certifying households earn 13.2% higher annualized transaction returns and sell at a 7.7% higher price.

[Insert Table VII About Here]

The findings in this section suggest that the information transmission under the peer effect is value-enhancing for focal households. They also highlight the role of financial motives in shaping the peer effect in residential green investments.

D. Green Preference and the Green-Peer Effect

The IMPLICATION 3 of the model suggests that while households with green preference are more likely to make residential green investments, the strength of green peer effect does not depend on their green preferences. I thus first investigate the association between the number of green homes and two proxies of green preference, and then examine whether the green-peer effect is heterogeneous in these proxies. The first proxy is the fraction of the adults in a county that is somewhat or very worried about global warming (Howe et al. (2015)) (*% Climate Worried*). The second proxy is the number of EVs per household at zip code level (*# EV per HH*), since environmentalists are more likely to adopt green practices (Kahn (2007)).

I use the following specification to examine the association between green homes and proxies for green preferences:

$$\%\ \text{Green Home}_{ct} = \alpha + \beta\, \text{Green Pref}_{ct} + \gamma\, \text{Controls}_{ct} + \theta_c + \theta_t + \epsilon_{ct}. \tag{28}$$

The controls include house price index, per capita income, median age, the percentage of people aged 25 and above with at least a college degree, and the natural logarithm of amount of the residential energy tax credit, number of new single-family homes, and population. The results of regressing the county- and zip code-level fraction of homes that are green certified on *% Climate Worried* and *# EV per HH* respectively are shown in columns (1) and (2) of Table VIII. We see that both the proxies of green preference are positively associated with the percentage of green homes, in line with IMPLICATION 3 (i) of the model.

[Insert Table VIII About Here]

I now examine heterogeneity in the green-peer effect by the degree of the proxies for green preference. To do this, I follow equation (25), where $\mathbb{1}(\text{High } \mathbf{X})$ now equals one for observations with above-county-year-median (above-zip code-year-median) values of *% Climate Worried* (*# EV per HH*). Columns (3) and (4) show the regression results. The insignificant coefficients of the interaction term indicate that the strength of the green-peer effect is statistically not different across areas with different degrees of green preferences, in line with IMPLICATION 3 (ii) of the model. This lack of heterogeneity also suggests that the green peer effect is not driven by green preferences alone.

E. Policy Implications

IMPLICATION 4 of the model suggests that under the current empirically estimated levels of peer effects, it is socially optimal to allocate more subsidies to areas with stronger peer effects. Several states and local governments run incentive programs encouraging green investments. I therefore shed light on efficiency of the spatial distribution of these programs in encouraging green investments by examining whether more regulatory incentives are available in areas with stronger peer effects. I divide the sample counties annually into deciles D_k, $k \in \{1,2,\ldots 10\}$ of estimated peer effects (statistically significant and positive at the 10% level or below) obtained from equation (22) and into an insignificant group D_ϕ. I then regress the number of regulatory incentives in a county in the current year (n_{ct}) separately on each $\mathbb{1}(D_k)$ in the previous year while including the base group D_ϕ using the following specification:

$$n_{ct} = \alpha + \beta \times \mathbb{1}(D_k)_{ct-1} + \gamma \,\text{Controls}_{ct} + \theta_t + \epsilon_{ct}; k \in \{1,2,\ldots 10\}, \text{base group: } D_\phi. \tag{29}$$

The controls include house price index, population in natural logarithm, per capita income, GDP growth, median age, and the percentage of people aged 25 and above with at least a college degree. θ_t represents year fixed effects.

Panel C in Figure 4 shows the regression coefficients for each decile. We see that contrary to the model prediction, the number of regulatory incentives in higher deciles are not significantly different from those in areas with no peer effects. I find similar patterns using other characteristics associated with peer effects. Specifically, the number of incentives is not correlated with two socioeconomic characteristics associated with stronger peer effects—social connectedness and social capital, as shown in Table IA.VI of Internet Appendix. Reducing this divergence from the model's prediction by adjusting the incentive provision may reduce the inefficiency. The finding suggests that the efficiency of the current distribution of the regulatory incentives in driving green technology adoptions could be further improved.

VI. Supplementary Results

This section present additional analyses that help contextualize the main findings.

A. Do residential green certifications represent real investments?

I first examine whether green certifications are associated with real investments in homes by using data on building permits, which are required for non-trivial home improvements. A building permit indicates both whether a non-trivial real investment is made in the home and also the value of the improvement (job value), making it an ideal measure of real investments in homes. In particular, energy-efficient upgrades related to green technologies including solar panels, efficient HVAC systems, and insulation of homes require a building permit. I regress a series of building permit-related variables on an indicator taking value of one for green-certified home in a sample of green and matched non-green homes using the following specification:[27]

$$y_{izt} = \alpha + \beta \times \text{Green}_{izt} + \gamma \text{ Controls} + \theta_z + \theta_t + \epsilon_{izt}. \tag{30}$$

θ_z and θ_t represent zip code and year-quarter fixed effects. The regression results are shown in Table IX. Columns (1) and (2) show that green-certified homes are significantly more likely than non-green homes to obtain building permits within one year prior to the certification. Additionally, columns (3) through (6) show that green homes tend to have a higher number of building permits and job values compared to non-green homes. Overall, the results suggest a positive relationship between green certification and real residential investments.

[Insert Table IX About Here]

To further reassure that the certifications represent real investments in green technologies, I utilize the data on residential energy tax credits (RETCs) from IRS. These tax credits are a direct and appropriate measure of residential green investments because households can claim these only if they undertake verifiable green improvements to their residences (IRS (n.d.)). Hence I examine whether the aggregate amount of tax credits claimed by households in a zip code is associated with the percentage of homes in the zip code that were newly green certified. I use the following specification:

$$y_{zt} = \alpha + \beta \times \% \text{ New Green Home}_{zt} + \gamma \text{ Controls}_{zt} + \theta_z + \theta_t + \epsilon_{zt}. \tag{31}$$

The controls include a series of zip code-level variables for housing market conditions and demographic characteristics: house price index, per capita income, median age,

[27] The sample for these regressions is constructed as follows. The green group G consists of all properties i that received green certification in year-quarter t between 2018 and 2022. The non-green group NG consists of the sample of properties selected by a random draw (with-replacement) of 50 non-green properties for every given property i that became green in year-quarter t (thus, non-green properties inherit the same value of t as the specific green property for which they were randomly drawn).

the percentage of people aged 25 and above with at least a college degree, and the natural logarithm of the number of new single-family homes and population. θ_z and θ_t represent zip code and year fixed effects.

Table X shows the regression results. We see that one percentage point increase in the percentage of newly green-certified homes is associated with a 7% increase in RETC (column (1)), a $1.26 increase in RETC per household (column (2)), and a 0.039 percentage point increase in the percentage of households filing for RETC (column (3)) respectively. In all, findings utilizing building permits and RETC indicate that green certifications are indeed associated with real investments.

[Insert Table X About Here]

B. Are the green investments just general home improvements that happen to incorporate newer, more efficient technologies?

An alternative interpretation of the green peer effect documented in this paper is that it merely reflects peer effects in general home improvements and is not specific to investments in green technologies. I address this concern by examining whether the peer effect is also present in home improvement decisions unrelated to green technologies. I classify building permits into five categories—HVAC, roofing, solar, windows and doors, and others. The last category includes normal kitchen renovations, pool construction, and landscaping etc. and is classified as non-green home improvements (Bellon et al. (2024)). I re-estimate the baseline model in a sample of home improvement decisions in this category and present the results in Table XI. We see that the peer effect does not exist for these non-green improvements, emphasizing that the informational issues are unique to residential green technologies and neighbor peers play a role in mitigating them.

[Insert Table XI About Here]

C. Is the green-peer effect merely a result of green clustering by builders?

An alternative mechanism for the green peer effect is that it arises from green features and amenities incorporated not by households, but by builders who tend to construct homes in bulk within a housing estate that may be spread across 0.1-mile area, resulting in clustering of green homes. In this case, the peer effects cannot be attributed to households. This concern is partly alleviated for several reasons. First, the estimation sample only includes properties whose certification year is different from its year built (as described in Section III), meaning that the certification is an intentional decision of the homeowners, not the builders. Second, a survey of builders and remodelers highlights that the biggest obstacle to build green homes is the lack of consumer demand (Dodge Data & Analytics (2020), p. 22–23), making it unlikely that green homes are built primarily as a result of anticipatory construction by builders. Third, to further address this concern, I repeat the baseline analysis by only including the green properties with a purchase transaction occurring at least two years prior to it becoming green and at least one building permit issued during this period. This restriction reassures that the certification is an intentional decision of the current homeowner. Table XII shows that the results still remain similar to the baseline results in Table II.

[Insert Table XII About Here]

D. Are investments in green technologies financially beneficial?

Even though peer effects can resolve informational issues regarding investments in residential green technologies, a rational household would not undertake the investments if doing so is not financially beneficial. Hence I examine whether such investments are financially beneficial by examining the difference in (i) returns on home improvements that are aimed at green certification and those that are not, and (ii) the resale value of green and non-green homes.

To estimate returns on home improvement investments that are aimed at green certification, I classify the home improvement loans that were taken within one year prior to the certification date as "green certification-targeted". To calculate the return, I take the bank-assessed property value at the time of the loan as the initial book value of the asset. I then calculate the asset's initial market value p_1 by dividing the book value by the ratio of the median bank-assessed value to the median sale price (market value) in the property's zip code in the month the loan was issued. The investment amount in this case is the loan amount c_1. To find the final market value of the asset, I use two proxies. The first proxy is the property's sale price in the subsequent transaction that occurs between three months and five years following the loan, adjusted for the growth of median sale price in the zip code p_2. The annualized return on investment for the homes undergoing resale transaction is $r_p = [(p_2 - p_1)/c_1]^{1/N} - 1$, where N is the duration from the loan date to the transaction date measured in years. The second proxy for the asset's final market value is property's assessed value in year $t+2$'s tax return a_{t+2}, adjusted for the growth of median assessed value in the zip code.[28] The

[28] For the assessed value, I use data from Corelogic. Owing to limited resources, I obtain this data only for Texas.

return on investment under this proxy is $r_a = (a_{t+2} - a_t)/c_1$. I then examine whether these returns are different for home improvements that are aimed at green certification from those that are not. Columns (1) and (2) of Table XIII respectively show that such home improvements earn 47.3% more in market price if the house is sold and 18.6% more in assessed value relative to the improvements that are not aimed at green certification.

[Insert Table XIII About Here]

I next estimate the difference in resale value of green homes and observationally equivalent non-green homes using the hedonic regression (26). Column (1) of Table XIV shows that green homes are associated with an average 2.4% increase in the sale value of a single-family property. A potential concern with this estimate is that the higher price reflects the value of additional investment incurred to make the house green. To address this, I re-estimate this equation by adding a control for home's assessed value assuming that tax appraisals account for all investments undertaken in the home. Controlling for the assessed improvement and land value, column (3) suggests that green homes fetch 4.9% higher house prices. In column (4), I examine the difference in county-year-level standard deviation of the residuals of house prices (unexplained by observed characteristics) for green and non-green homes. The result suggests that house prices of green homes are less volatile relative to non-green homes, implying that they are less risky assets.

[Insert Table XIV About Here]

Taken together, I find that investing in a green home is on average financially beneficial and the market prices are less volatile. My findings do not contradict those of Fowlie, Greenstone, and Wolfram (2018), who show that energy efficiency investments under the subsidized Weatherization Assistance Program (WAP) in Michigan yielded negative financial returns. Their empirical context is different from mine in several crucial aspects. First, they focus on a government subsidized program targeted to low-income households in Michigan, whereas I focus on green certification programs available to households regardless of their income across the US. Second, the focus of WAP is on energy efficiency, whereas that of green certifications is on broader sustainability measures including air quality and water conservation, expanding the scope of potential benefits of green investments. Third, the associated industry (contractors, supplier, financier etc.) and the recognition of the value of green homes by the market have evolved significantly since their study.

E. Is the green-peer effect driven by "keeping-up-with-the-Joneses" motive?

"Keeping-up-with-the-Joneses" motive is a common alternative mechanism purposed for peer effects (Abel (1990), Gali (1994), Campbell and Cochrane (1999), Hong et al. (2014), Heimer (2016)). It hypothesizes that one acquires a product simply to satisfy the desire to "keep up with the Joneses", even if it lowers their overall well-being. Several of the findings discussed previously contradict this mechanism. First, consider the pattern in Panel A and B of Figure 4. There is a hump-shaped relation between the green peer effect and the fraction of within 0.5-mile homes that are green. If the peer effect were driven by this alternative motive, its strength would not decrease with higher level of adoptions. Second, if the green investment decision were driven by this alternative motive, the decision would be insensitive to whether doing so is financially beneficial, making the peer effect also insensitive to potential financial benefits of green investments. However, the results in Table VI show that the peer effect is heterogeneous in potential financial benefits, contradicting the "keeping-up-with-the-Joneses" motive. In all, this alternative motive appears unlikely to be the dominant mechanism behind the peer effect.

F. Is the green-peer effect driven by conspicuous consumption utility (visual inference)?

The green-peer effect may also be driven by conspicuous consumption, where households infer the investment or consumption of their neighbors through visible observation, rather than information transmission through direct interactions (Hopkins and Kornienko (2004), Charles, Hurst, and Roussanov (2009), Han, Hirshleifer, and Walden (2023)). Since displaying the green certificate is not required by the programs, the visible observation by the neighboring households is less likely. However, some types of green technologies such as solar panels are more visible than others like advanced insulation or energy-efficient windows, exposing the neighboring households without explicit social interactions and information transmission. To understand this alternative mechanism, I test heterogeneity in peer effects by the degree of conspicuousness of residential green technologies. If conspicuous consumption is the dominant mechanism, peer effects would be stronger in areas where conspicuousness is high. For this test, I replace the term $\mathbb{1}(High\ \mathbb{X})$ in equation (25) with the census-tract-level degree of conspicuousness of green certifications ($\mathbb{X}$). I measure conspicuousness in three ways and show the regression results in Table XV. In column (1) it is an indicator equal to one for properties in census tracts with at least one solar building permit. In column (2) it is an indicator equal to one for census-tract-year level above-median percentage of properties with solar building permits. In column (3), it is an indicator equal to one for census tract-quarters that experience over the last four quarters (inclusive of current quarter) above-median percentage of green certifications from programs that explicitly require photovoltaic (PV) solar generation.[29] All the three interaction terms are statistically insignificant, indicating an absence of heterogeneity in the peer effects by degree of conspicuousness of green investments. Thus, conspicuous consumption is not the key driver of the green peer effect.

[Insert Table XV About Here]

VII. Conclusion

Informational issues among households have been argued to be a key barrier limiting the wider adoption. In this paper I study the role of neighbors in households' decision to invest in residential green technologies. I build a theoretical model of peer effects utilizing a discrete choice model under social interactions and empirically test its predictions using highly granular nationwide data on single-family homes combined with novel data on homes' green certification records that allows to identify residential green investments by households. I use a nearest-neighbor research design to draw causal conclusion about peer effects in residential green investments. I find that households are 1.6 times more likely to make green investments to their home for each additional neighbor within 0.1 miles who has done so in the past year, relative to a household with no such neighbor. I show that this influence of immediate green neighbors also extends to focal households' secondary properties located in faraway neighborhoods, emphasizing that neighbors act as a source of information in focal households' green investment decisions. The peer effect is more pronounced in areas where green homes enjoy financial benefits in terms of higher house prices, electricity savings, and regulatory incentives relative to non-green homes; in contrast, it remains similar across counties varying in households' green preferences. Furthermore, the housing return on homes green certified by green-exposed households is higher than on homes that remain non-certified despite being similarly green exposed. Finally, I find that the distribution of the number of regulatory incentives across areas does not align with the theoretical distribution corresponding to socially optimum adoption.

[29] These programs are Built Green, Earth Advantage, Florida Green Building Coalition, Green Built Homes, GreenPoint Rated, Home Energy Score, LEED for Homes, National Green Building Standard, and Zero Energy Ready Home. Despite considering PV solar generation in its certification criteria, since HERS accounts for more than 90% of all certifications, it is not included in this list to preserve geographic variations in conspicuousness.

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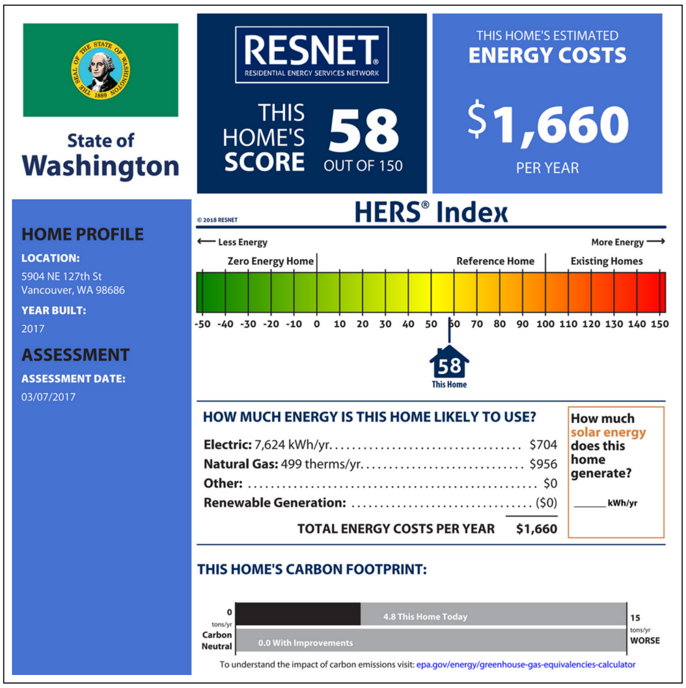
(A) HERS Program Homes



(B) HES Program

(C) Word Cloud of Certification Reports

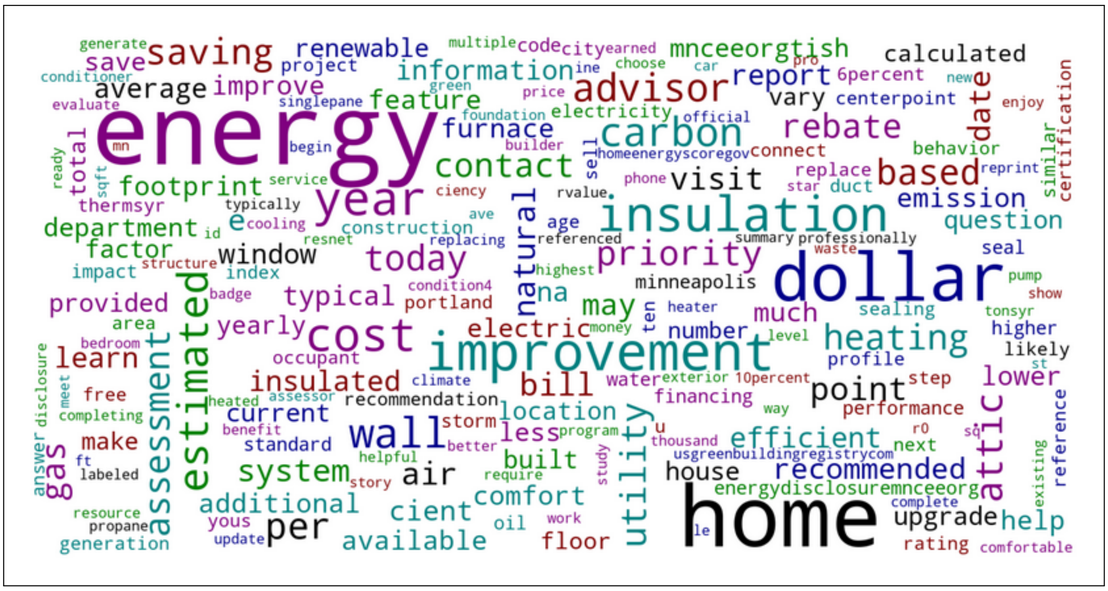
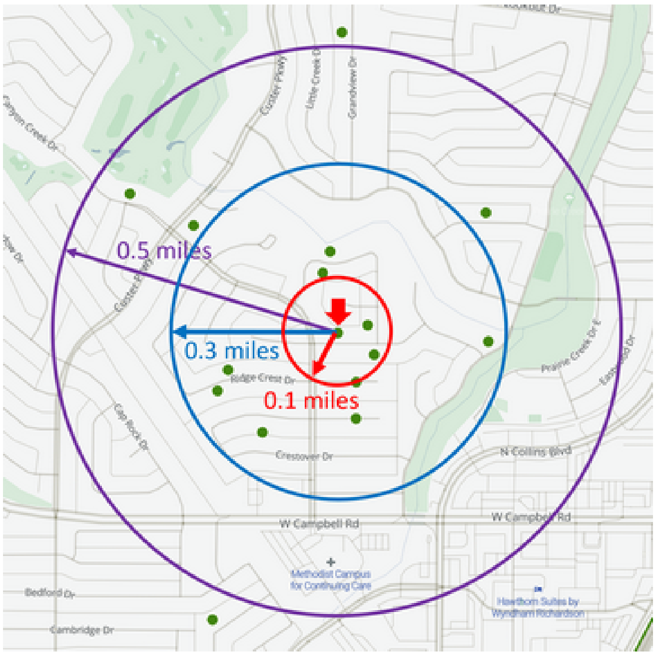


Figure 1. Sample Green Certification Reports. This figure shows the certification reports issued by the two most common green certification programs in the US—HERS and HES—in Panel A and B respectively. The reports include information on property location, date of certification, and energy profile of the home. Panel C presents a word cloud generated from the 200 most frequently used words in the certification reports.

(A) Green Neighbors around a Green Focal Property



(B) Green Neighbors around a Non-green Focal Property

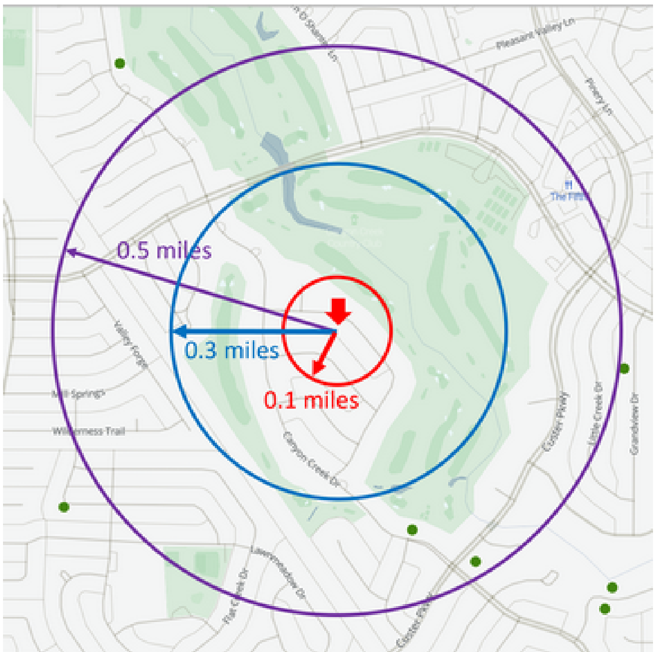


Figure 2. Illustration of the Nearest-Neighbor Research Design. Panel A shows an example of a green focal property in Dallas (pointed to by the red arrow) and the number of its green neighbors within 0.1-, 0.3- and 0.5-mile rings (shown as green dots). Panel B shows an example of a non-green focal property in Dallas (pointed to by the red arrow) and the number of its green neighbors within 0.1-, 0.3- and 0.5-mile rings (shown as green dots).

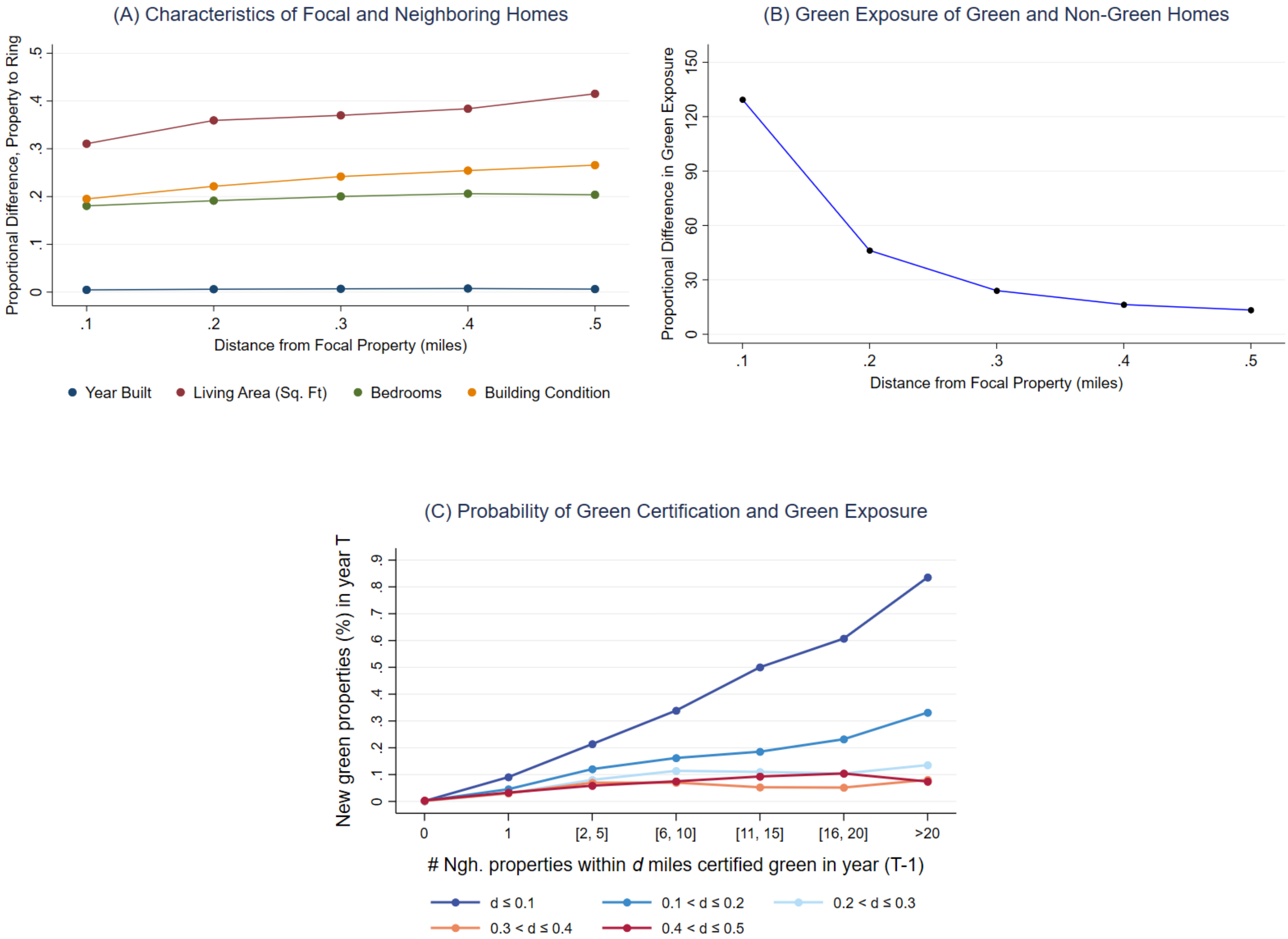


Figure 3. Spatial Variation in Home Characteristics, Green Exposure, and Certification Probability. Panel A plots the average proportional difference in property characteristics defined in equation (20). Panel B shows the average proportional difference in green exposure defined in equation (21) of green-certified properties (G) and non-green properties (NG). Panel C plots on the y-axis the average probability of a household green certifying the property against the number of neighbors located within d miles who have green certified their homes in the past year. The average probability is calculated in quarter q for each bin (of the number of green neighbors) and for each distance ring d as the ratio of the number of properties that are green certified for the first time in quarter q to the total number of properties (in respective bin and ring) that have not become green until quarter $q-1$. The mean of these average probabilities across quarters is plotted in percentages on the y-axis.

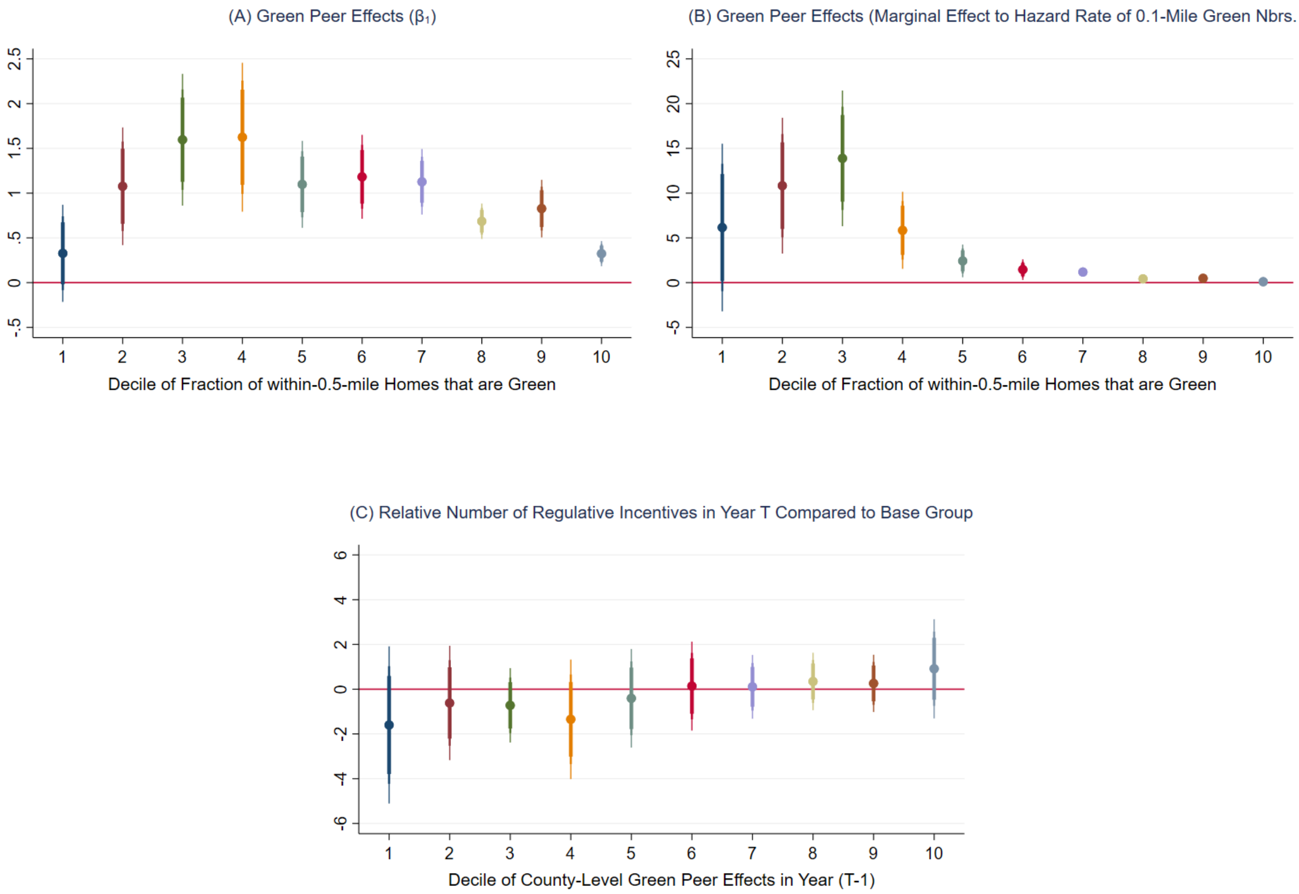


Figure 4. Green Peer Effects, Already-Adopting Neighbor Peers and Regulatory Incentives. Panel A and B show the green peer effects estimated separately using equation (22) in each decile of the fraction of within-0.5-mile homes that are green, and Panel C shows the relation between the levels of regulative incentives and the strength of green peer effects. Panel A plots β_1—the coefficient on $N_G(\leq 0.1\ mi)$ from equation (22)—on the y-axis. Panel B plots the *Marginal Effect to Hazard Rate*—the ratio of the coefficient on $N_G(\leq 0.1\ mi)$ to the regression intercept—on the y-axis. The deciles in Panel A and B are calculated among the sample of 0.5-mile rings with at least one green home. In Panel C, the x-axis plots the deciles of green peer effects in year $t-1$. Green peer effects are measured using the separately estimated β_1 for each county and year in equation (22) that is statistically significant and positive at the 10% level or below. The relative number of county- and state-level regulatory green incentives compared to base group—the county-year observations with zero or insignificant β_1— is plotted on the y-axis.

Table I
Summary Statistics

This table reports the summary statistics. Panel A reports the summary statistics of the property×year-quarter level green status and green exposures. *Green* is an indicator that takes on a value of 10,000 (for readability) if household i obtains the first-ever green certificate for his or her property in quarter t. $N_G(\leq d\ mi)$ measures how many neighbors of the household became green for the first time within d miles to the focal property over the previous four quarters (inclusive of the current quarter), where $d \in \{0.1, 0.3, 0.5\}$. Panel B reports the summary statistics of property characteristics. *Green* at the property level is an indicator that takes on a value of 10,000 (for readability) if the property has been green certified during the sample period. *Year Built* is the year in which the property was constructed. *Living Area (square feet)* is the living area of the property in square feet. *# Bedrooms* is the number of bedrooms in the property. Panel C reports the summary statistics of neighborhood characteristics. *# Incentives* is the number of regulatory green incentives at both county and state-level. *% Climate Worried* measures the percentage of population in a county who are worried about climate change. *Annual Price Growth* is the annual change of the housing price index of a census tract. *Housing Density* is the number of residential properties per acre in a census tract. *AGI ($1,000) Per Capita* is the adjusted gross income (reported in thousands of dollars) per person at the zip code level.

Variable	Obs.	Mean	Median	Std. Dev.
Green Status and Exposures (Panel: Property×Year-Quarter)				
Green (=10,000)	1,037,652,080	0.40	0	63.18
$N_G(\leq 0.1$ mi)	1,037,652,080	0.09	0	2.92
$N_G(\leq 0.3$ mi)	1,037,652,080	0.37	0	4.45
$N_G(\leq 0.5$ mi)	1,037,652,080	0.62	0	5.83
Property Characteristics (Panel: Property level)				
Green (=10,000)	56,546,251	7.47	0	273.12
Year Built	56,546,251	1,974.70	1,978	28.71
Living Area (square feet)	56,546,251	1,855.41	1,680	777.04
# Bedrooms	56,399,493	2.49	3	1.55
Neighborhood Characteristics (Panel: Varies)				
# Incentives	21,216	3.68	3	3.49
% Climate Worried	13,056	53.87	53	7.09
Housing Density	738,043	2.06	1	3.36
Annual Price Growth (%)	1,672,032	4.52	4	8.82
AGI ($1,000) Per Capita	227,336	33.96	28	29.46

Table II
Peer Effects of Green Neighbors on Residential Green Investments

This table reports the effect of green neighbors on the decision of a focal household to also invest in residential green technologies. The regression specification is from equation (22). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. *Marginal Effect to Hazard Rate* is equal to the ratio of the associated coefficient to the intercept. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1$ mi)	0.69***	0.33***	0.37***	0.38***
	(0.06)	(0.05)	(0.05)	(0.05)
$N_G(\leq 0.3$ mi)		0.27***	0.23***	0.22***
		(0.02)	(0.02)	(0.02)
$N_G(\leq 0.5$ mi)		0.08***	0.06***	0.06***
		(0.01)	(0.01)	(0.01)
Constant	0.32***	0.21***	0.23***	0.23***
	(0.01)	(0.01)	(0.01)	(0.01)
Marginal Effect to Hazard Rate				
$N_G(\leq 0.1$ mi)	2.18***	1.58***	1.78***	1.82***
	(0.19)	(0.28)	(0.27)	(0.27)
Fixed effects	N	N	Zip code, YQ	Zip code × YQ
R^2 (Adj.)	0.0010	0.0014	0.0021	0.0033
Observations	1,037,652,080	1,037,652,080	1,037,652,076	1,037,641,505

Table III
Information Transmission: Peer Effects and Multi-Property Owners

This table reports green-peer effects observed from primary home of MPOs to their secondary properties. The sample in columns (1) and (2) includes the secondary properties in the top quartile of similarity to their neighbors located within 0.1 miles of the primary homes. This similarity is calculated using Gower's distance, based on property age, living area, exterior materials, heat type and roof materials; and in columns (3) and (4) includes those in the bottom quartile of the similarity. The regression specification follows equation (22) and includes the green exposures from neighbors of both primary home ($N_G(\leq d\ mi)_{Primary\ Home}$) and secondary property ($N_G(\leq d\ mi)_{Secondary\ Property}$) for all three rings. In columns (1) and (3) the distance between the primary–secondary pairs is more than 20 miles, and in columns (2) and (4), 50 miles. All models include primary zip code, secondary zip code, owner and year-quarter fixed effects. Standard errors are clustered by primary residence zip code×year-quarter and secondary property zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Secondary Property Green (=10,000)			
Secondary Property-Primary Nbrs Similarity:	[Top Quartile]		[Bottom Quartile]	
	(1)	(2)	(3)	(4)
Primary to Secondary Distance	>20 mi	>50 mi	>20 mi	>50 mi
$N_G(\leq 0.1\text{ mi})_{\text{Primary Home}}$	0.010**	0.010**	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
$N_G(\leq 0.1\text{ mi})_{\text{Secondary Property}}$	0.073*	0.080*	0.035	0.036*
	(0.04)	(0.05)	(0.02)	(0.02)
0.3- & 0.5-mi $N_{G,\text{ Primary Home}}$	Y	Y	Y	Y
0.3- & 0.5-mi $N_{G,\text{ Secondary Property}}$	Y	Y	Y	Y
Primary zip code FE	Y	Y	Y	Y
Secondary zip code FE	Y	Y	Y	Y
YQ FE	Y	Y	Y	Y
R^2 (Adj.)	0.1175	0.1154	0.1039	0.0989
Observations	16,228,739	15,335,946	24,882,976	24,660,686

Table IV
Peer Commonalities in Choice of Certification Programs, Investment, and Lenders

This table reports the results of regressing similarity measures of green investment decisions of focal household-neighbor pairs on an indicator for within-0.1-mile neighbors, where the omitted category is 0.1-to-0.5-mile neighbors. The outcome variable in columns (1) and (2) is one when a focal household×neighbor pair has the same green certificate ($\mathbb{1}$(Same Cert.)); in column (3) is textual cosine similarity of green certificates; in column (4) is textual cosine similarity of building permits; and in columns (5) and (6) is one when a focal household×neighbor pair has the same mortgage lender ($\mathbb{1}$(Same Lender)). The indicator $\mathbb{1}$(Dist. $\leq$ 0.1 mi) is one when the distance between focal household and neighbor is within 0.1 miles. The sample in column (1) includes all certificates; in column (2) excludes the most common certificate (HERS); in column (3) includes all such neighbor pairs whose green certificates are issued under the same program and downloadable from GBR website; in column (4) includes all building permits obtained by the green neighbor pairs within one year prior to their own green certification dates; in column (5) includes all lenders; and in column (6) excludes the top three lenders in terms of loan amount requested in mortgage applications in a county-year. All regressions include focal property's tenure and zip code×year-quarter fixed effects. Standard errors are clustered by focal zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Similarity in:	Program Choice		Investment Choice		Lender Choice	
Outcome:	$\mathbb{1}$(Same Program)		Text Cosine Similarity		$\mathbb{1}$(Same Lender)	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	[All Prog]	[Ex Top Prog]	[Certificate]	[Bldg. Permit]	[All Lender]	[Ex Top 3 Lender]
$\mathbb{1}$(Dist. $\leq$ 0.1 mi)	0.005***	0.011***	0.020***	0.056**	0.094***	0.100***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)
Focal tenure FE	Y	Y	Y	Y	Y	Y
Focal zip code × YQ FE	Y	Y	Y	Y	Y	Y
R^2 (Adj.)	0.5228	0.5929	0.7093	0.2619	0.3817	0.3808
Observations	7,338,920	787,273	90,971	9,138,633	22,007	17,998

Table V
Effect Heterogeneity by Strength of Local Community Interactions

This table reports the heterogeneous green-peer effects by the strength of local community interactions using equation (25). The outcome variable *Green* (=*10,000*) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. The measure of the strength of local community interactions ($\mathbb{X}$) in the four columns are respectively: social connectedness, support ratio, social capital, and % investment properties. $\mathbb{1}$(High $\mathbb{X}$) is a 0/1 indicator for observations with above-median values of the respective characteristic $\mathbb{X}$. The bottom row in the column header denotes the level at which the median for respective characteristic $\mathbb{X}$ is calculated. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. All the models control for outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}$(High $\mathbb{X}$) $\times N_G(\leq d\ mi)$). All these variables are defined in Table I. All the models include zip code and year-quarter fixed effects. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
Characteristic $\mathbb{X}$:	Social Connectedness	Support Ratio	Social Capital	% Investment Properties
[Median of $\mathbb{X}$ calculated at:]	[zip code]	[zip code]	[county]	[zip code × yq]
$\mathbb{1}$(High $\mathbb{X}$) × $N_G(\leq 0.1$ mi$)$	0.387*	0.401***	0.537***	-0.190*
	(0.22)	(0.13)	(0.11)	(0.11)
$N_G(\leq 0.1$ mi$)$	0.445***	0.438***	0.360***	0.554***
	(0.05)	(0.05)	(0.05)	(0.09)
$\mathbb{1}$(High $\mathbb{X}$)			-0.111**	0.074***
			(0.04)	(0.03)
Level: 0.3- & 0.5-mi N_G	Y	Y	Y	Y
Interaction: 0.3- & 0.5-mi N_G	Y	Y	Y	Y
FE: zip code and YQ	Y	Y	Y	Y
R^2 (Adj.)	0.0024	0.0023	0.0021	0.0021
Observations	937,546,288	1,018,429,013	1,037,652,076	1,037,652,076

Table VI
Effect Heterogeneity by Green Home Benefits

This table reports the heterogeneous green-peer effects across counties with or without green home benefits. The outcome variable *Green* (*=10,000*) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. The indicator $\mathbb{1}(\mathbb{B}$ exists$)$ in column (1) is a county×year variable taking the value of one when the coefficient on $Green_{it}$ in equation (26) is statistically significant and positive at the 10% level or below; in column (2) is a territory×year indicator taking the value of one for above-median levels of utility service territory-level electricity prices; and in column (3) is a county×year-quarter variable taking the value of one for above-median number of regulatory incentives. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring $d = 0.1$, 0.3 and 0.5 miles. All the models control for outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{1}(\mathbb{B}$ exists$) \times N_G(\leq d\ mi)$). All these variables are defined in Table I. All the models include zip code and year-quarter fixed effects. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	(1)	(2)	(3)
Benefit ($\mathbb{B}$) in terms of:	House Prices	Electricity Prices	Incentives
$\mathbb{1}(\mathbb{B}$ exists$) \times N_G(\leq 0.1$ mi$)$	0.668***	0.339***	0.970***
	(0.24)	(0.10)	(0.10)
$N_G(\leq 0.1$ mi$)$	0.337***	0.123*	0.359***
	(0.04)	(0.06)	(0.06)
$\mathbb{1}(\mathbb{B}$ exists$)$	0.155***	-0.081***	-0.162***
	(0.06)	(0.03)	(0.04)
Level: 0.3- & 0.5-mi N_G	Y	Y	Y
Interaction: 0.3- & 0.5-mi N_G	Y	Y	Y
FE: zip code and YQ	Y	Y	Y
R^2 (Adj.)	0.0022	0.0015	0.0023
Observations	303,576,068	874,272,556	983,212,581

Table VII
Peer-induced Green Certifications and Housing Transaction Returns

This table reports the effect of the green certification decision on the housing market returns of the green-exposed households. The regression sample includes two sets of households. The first set consists of those who obtained green certificates and have at least one green neighbor within 0.1-mile distance in the past year at the time of certification. The second set includes randomly drawn (with replacement) non-green but similarly exposed (i.e., at least one green neighbor within 0.1-mile distance in the past year) households. The outcome variable in column (1) is the annualized rate of return on properties observed to be sold by the peer-influenced households, trimming outliers greater than 200 percent. The outcome variable in column (2) is the implied residual at the time of sale relative to expected market rate as measured by a county-level quarterly price index. The indicator ($\mathbb{1}$(Green)) takes the value of 1 for the households who obtain a green certificate during their tenure at the property. All the models include year of purchase, sale, and green certification fixed effects. Standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)
Outcome:	Return	Sell Residual
$\mathbb{1}$(Green)	0.132***	0.077***
	(0.01)	(0.01)
Buy year FE	Y	Y
Sell year FE	Y	Y
Green year FE	Y	Y
R^2 (Adj.)	0.0624	0.0128
Observations	14,860	14,859

Table VIII
Green Preference, Green Certifications, and Heterogeneous Peer Effects

Columns (1) and (2) of this table report the results of regressing the share of green homes on green preferences. Columns (3) and (4) report the heterogeneous green-peer effects across areas with different degrees of green preference. The outcome variable in columns (1) and (2) is the ratio of the number of residential properties that are green certified in a year in an area (*% Green Home*); and in columns (3) and (4) is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property (*Green (=10,000)*). *% Climate Worried* is the percentage of adults in a county who are worried about climate change. *# EV per HH* is the number of EV per household at zip code level. Indicator $\mathbb{1}(\text{High }\mathbb{X})$ is one for above-median area×year values of the respective characteristic $\mathbb{X}$—*% Climate Worried* and *# EV per HH*. Columns (1) and (2) include *Housing mkt. & demog. controls*, which consists of the amount of the residential energy tax credit, house price index, number of new single-family homes, population, per capita income, median age, and the percentage of people aged 25 and above with at least a college degree. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. Columns (3) and (4) include controls for $\mathbb{1}(\text{High }\mathbb{X})$, outer ring green exposure ($N_G(\leq d\ mi)$), and the respective interaction terms ($\mathbb{1}(\text{High }\mathbb{X}) \times N_G(\leq d\ mi)$). All these variables are defined in Table I. Standard errors are reported in parentheses, and the level of clustering is listed at the bottom of the table. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	% Green Home		Green (=10,000)	
	(1)	(2)	(3)	(4)
% Climate Worried	0.047***			
	(0.01)			
# EV per HH		1.314*		
		(0.69)		
$\mathbb{1}$(High % Climate Worried) × $N_G(\leq 0.1$ mi)			-0.018	
			(0.12)	
$\mathbb{1}$(High # EV per HH) × $N_G(\leq 0.1$ mi)				-0.108
				(0.14)
$N_G(\leq 0.1$ mi)			0.460***	0.773***
			(0.09)	(0.10)
Level: $\mathbb{1}(\text{High }\mathbb{X})$	-	-	Y	Y
Level: 0.3- & 0.5-mi N_G	-	-	Y	Y
Interaction: 0.3- & 0.5-mi N_G	-	-	Y	Y
Housing mkt. & demog. controls	Y	Y	-	-
Fixed effects	County, Year	Zip code, Year	Zip code, YQ	Zip code, YQ
Clustering level	County	Zip code	Zip code × YQ	Zip code × YQ
Observation unit	County	Zip code	Property	Property
R^2 (Adj.)	0.8247	0.7970	0.0020	0.0020
Observations	11,233	48,596	821,323,588	348,127,621

Table IX
Building Permits and Green Homes

This table reports the results of regressing building permits obtained before certification on green status of the properties. The sample consists of green properties (G) and randomly selected non-green properties (NG). The outcome variables are: (i) an indicator that takes the value of one if household i obtained at least one building permit for their property within the four quarters prior to year-quarter q (in columns (1) and (2)); (ii) the number of building permits obtained within the same four-quarter period (in columns (3) and (4)); and (iii) the job value of the building permits obtained within the same four-quarter period (in columns (5) and (6)). *Green* is an indicator taking the value of one for green certified properties. The control variables include property age, living area, # bedrooms. The sample is constructed as follows. The green group G consists of all properties j that received green certification in year-quarter q between 2018 and 2022. The non-green group NG consists of the sample of properties selected by a random draw (with-replacement) of 50 non-green properties for every given property j that became green in year-quarter q (thus, non-green properties inherit the same value of q as the specific green property for which they were randomly drawn). Standard errors are clustered by zip code and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	$\mathbb{1}$(Obtained Bldg. Permit)		# Bldg. Permit		Ln(Job Value)	
	(1)	(2)	(3)	(4)	(5)	(6)
Green	0.591***	0.582***	1.987***	1.820***	2.172***	1.770***
	(0.01)	(0.01)	(0.04)	(0.04)	(0.08)	(0.08)
Controls	N	Y	N	Y	N	Y
Zip code FE	Y	Y	Y	Y	Y	Y
YQ FE	Y	Y	Y	Y	Y	Y
Model	OLS	OLS	PPML	PPML	OLS	OLS
R^2 (Adj.)	0.1001	0.0991	0.1498	0.1535	0.3728	0.4106
Observations	7,739,539	7,725,367	7,720,868	7,706,771	564,748	561,005

Table X
Residential Energy Tax Credits Incentives and Green Homes

This table reports the results of regressing the residential energy tax credits (RETC) claimed by households to the Internal Revenue Service (IRS) on residential green certifications in a zip code. The outcome variables in column (1) through (3) are respectively zip code-level residential energy tax credit amount in natural logarithm ($Ln(A_{RETC})$), residential energy tax credit amount per household (A_{RETC}/# *Household*), and the percentage of households filing for residential energy tax credits (*RETC Households* (%)). % *New Green Home* is the percentage of residential properties that were newly green certified in a zip code in a year. Control variables include zip code-level house price index, the number of new single-family homes, population, per capita income, median age, and the percentage of people aged 25 and above with at least a college degree. All the models include zip code and year fixed effects. Standard errors are clustered by zip code and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1) $\text{Ln}(\text{A}_{\text{RETC}})$	(2) $\frac{\text{A}_{\text{RETC}}}{\text{\# Households}}$	(3) RETC Households (%)
% New Green Home	0.070***	1.263***	0.039***
	(0.01)	(0.26)	(0.01)
Housing mkt. & demog. controls	Y	Y	Y
Fixed effects	Zip code, Year	Zip code, Year	Zip code, Year
R^2 (Adj.)	0.8567	0.6484	0.7771
Observations	148,800	189,868	189,868

Table XI
Placebo Test: Peer Effects of Exposure to Non-Green Residential Investments

This table reports the effect of neighbors on the decision of a focal household to also invest in residential, non-green technologies, where such investments are proxied by building permits. Using standard string parsing methods, permits are categorized into five groups: HVAC, Roofing, Solar, Windows and Doors, and Other. The outcome variable *Non-Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a focal household obtains the first building permit in the "Other" category for his/her property. $N_G(\leq d\ mi)_{\textbf{\textit{Non-Green}}}$ is the exposure measured as the number of neighbors who have obtained building permits in the "Other" category over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. *Marginal Effect to Hazard Rate* is equal to the ratio of the associated coefficient to the intercept. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Non-Green (=10,000)		
	(1)	(2)	(3)
$N_G(\leq 0.1\text{ mi})_{\text{Non-Green}}$	-0.12	-0.26	-0.73**
	(0.28)	(0.31)	(0.31)
$N_G(\leq 0.3\text{ mi})_{\text{Non-Green}}$	-3.16***	-2.11***	0.01
	(0.50)	(0.54)	(0.40)
$N_G(\leq 0.5\text{ mi})_{\text{Non-Green}}$	3.55***	2.68***	0.75***
	(0.29)	(0.30)	(0.12)
Fixed effects	N	Zip code, YQ	Zip code × YQ
R^2 (Adj.)	0.0067	0.0171	0.0356
Observations	81,740,448	81,740,441	81,734,269

Table XII
Baseline Estimates for Subsample of Green Homes with Prior Purchase Transaction

This table shows the baseline estimates of Table II for the subsample of green homes with a known purchase transaction that occurred at least two years prior to the date of green certification and at least one building permit issued within this time period. The regression specification is from equation (22). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	(1)	(2)	(3)
$N_G(\leq 0.1$ mi)	0.32***	0.36***	0.36***
	(0.05)	(0.05)	(0.05)
$N_G(\leq 0.3$ mi)	0.18***	0.14***	0.14***
	(0.01)	(0.01)	(0.01)
$N_G(\leq 0.5$ mi)	0.06***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)
Fixed effects	N	Zip code, YQ	Zip code × YQ
R^2 (Adj.)	0.0014	0.0023	0.0033
Observations	1,037,584,050	1,037,584,046	1,037,573,475

Table XIII
Returns of Green versus Non-Green Home Improvements

This table reports the results of regressing investments returns on green status for a sample of properties which had home improvement loans. The outcome variable is the annualized return on house transaction price in column (1) and return on assessed value of the property in column (2). *Green* is an indicator taking the value of one for the home improvement loans that were followed by a green certification of the underlying property within a year. The sample in column (1) includes house sales across the US during year 2018 and 2022, and in column (2) includes homes in Texas only. Control variables include property age, living area, # bedrooms, exterior materials, heat type, roof materials. Standard errors are clustered by county and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome: Investment Return	r_p	r_a
	(1)	(2)
Return calculated using:	Transaction Price (US)	Assessed Value (TX only)
Green	0.473^{*}	0.186^{***}
	(0.27)	(0.05)
Regression panel	Loan	Loan
Controls	Y	Y
Fixed effects	Zip code, Year	Zip code, Year
R^2 (Adj.)	0.06	0.04
Observations	18,626	6,876

Table XIV
Price and Risk of Green versus Non-Green Homes

This table reports the results of regressing house prices in natural logarithm in columns (1) through (3) and county-year level standard deviation of residualized house prices in column (4) on green status. The residuals are obtained from the following repeat-sale regression estimated separately for each county: $\ln(\text{Price})_{int} = a_{in} + \delta_t + \theta_n + \mathbb{1}(\text{Non-Person Buyer})_{int} + \mathbb{1}(\text{Non-Person Seller})_{int} + \epsilon_{int}$. Here the outcome variable is the natural logarithm of transaction price occurring in year-quarter t of property i's n−th transaction. a_{in}, δ_t and θ_n respectively represent fixed effects for property, year-quarter and transaction sequence (five or more transactions are grouped together). *Green* is an indicator of the property's green status at the time of transaction. Green homes are restricted to those green certified within two years prior to the transaction, while non-green homes are not certified at the time of transaction. The sample in columns (1) and (4) includes sales by individual buyers and sellers across the US during year 2018 and 2022, whereas in columns (2) and (3) includes those in Texas. The control variables in columns (1) to (3) include property age, living area, # bedrooms, exterior materials, heat type, roof materials, an indicator of mortgage-financed purchase, mortgage term, and mortgage interest rate. Column (3) includes the assessed improvement value and assessed land value as additional controls. Standard errors are clustered at the zip code level in columns (1) through (3) and at the county level in column (4), and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Sample:	Home Sales (US)	Home Sales (TX)		Home Sales (US)
	(1)	(2)	(3)	(4)
Outcome:	Ln(Price)	Ln(Price)	Ln(Price)	SD(Residual)
Green	0.024***	0.072***	0.049***	-0.041***
	(0.00)	(0.01)	(0.01)	(0.01)
Ln(Assessed Improv. Value)			0.352***	
			(0.01)	
Ln(Assessed Land Value)			0.221***	
			(0.01)	
Controls	Y	Y	Y	N
Zip code FE	Y	Y	Y	-
County FE	-	-	-	Y
Year FE	Y	Y	Y	Y
R^2 (Adj.)	0.73	0.65	0.70	0.54
Observations	6,096,075	204,818	204,818	13,414

Table XV
Effect Heterogeneity by Conspicuous Green Investments

This table reports the heterogeneous green-peer effects by degree of conspicuousness of green investments. Conspicuousness $\mathbb{X}$ in column (1) is an indicator equal to one for properties in census tracts with at least one solar building permit ($\mathbb{1}$(*Solar Permit?*)); in column (2) is an indicator equal to one for census-tract-year level above-median percentage of properties with solar building permits ($\mathbb{1}$(*High Solar Permit* %)); and in column (3) is an indicator equal to one for census-tract-year level above-median percentage of green certifications from programs explicitly requiring photovoltaic (PV) solar generation over the last four quarters ($\mathbb{1}$(*High Grn Bldg. w/ Solar Program* %)). The programs that include PV are Build Green, Earth Advantage, Florida Green Building Coalition, Green Built Homes, GreenPoint Rated, Home Energy Score, LEED for Homes, National Green Building Standard, and Zero Energy Ready Home. Note that the HERS program is excluded from this ratio even though it considers PV solar generation in its certification, because it dominates the certifications (94%). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. All the models control for outer ring green exposure ($N_G(\leq d\ mi)$) and the respective interaction terms ($\mathbb{X} \times N_G(\leq d\ mi)$). All these variables are defined in Table I. All the models include zip code and year-quarter fixed effects. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	(1)	(2)	(3)
Conspicuousness $\mathbb{X}$ =	$\mathbb{1}$(Solar Permit?)	$\mathbb{1}$(High Solar Permit %)	$\mathbb{1}$(High Grn Bldg. w/ Solar Program %)
$\mathbb{X} \times$ N$_G$($\leq$ 0.1 mi)	-0.105	-0.146	0.057
	(0.11)	(0.11)	(0.38)
N$_G$($\leq$ 0.1 mi)	0.422***	0.383***	0.638***
	(0.09)	(0.08)	(0.20)
$\mathbb{X}$	0.012	0.155***	0.101
	(0.03)	(0.05)	(0.15)
Level: 0.3- & 0.5-mi N$_G$	Y	Y	Y
Interaction: $\mathbb{X} \times$ 0.3- & 0.5-mi N$_G$	Y	Y	Y
FE: zip code and YQ	Y	Y	Y
R^2 (Adj.)	0.0024	0.0025	0.0030
Observations	334,626,734	201,078,467	88,681,649

Internet Appendix to
"Green Neighbors, Greener Neighborhoods: Peer Effects in Residential Green Investments"

Christine Zhuowei Huang*

Abstract

This Internet Appendix provides additional proofs, data processing, tables, and figures supporting the main text.

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A. Derivation of Key Equations

1. Proof of Equation (19)

Total differentiation of equation (18) and rearranging gives the following:

$$\frac{dS_i}{dv_1} = m_i^S + (v_1 + v_2 K_a)\frac{dm_i^S}{dv_1}. \tag{IA.1}$$

From equations (11) and (16), the expected adoption rate of neighbors for household i is given by:

$$m_i^S = \frac{1}{1 + exp(-Z_i)}, \text{ where } Z_i = \Pi_i(\cdot) - C_i(\cdot) - F_1 - F_2 + 2(v_1 + v_2 K_a)m_i^S. \tag{IA.2}$$

Using the derivative of the logistic function and applying the chain rule, we have:

$$\frac{dm_i^S}{dv_1} = \frac{dm_i^S}{dZ_i}\frac{dZ_i}{dv_1} = m_i^S(1 - m_i^S)\left[2(v_1 + v_2 K_a)\frac{dm_i^S}{dv_1}\right]. \tag{IA.3}$$

Rearranging to solve for $\frac{dm_i^S}{dv_1}$, we get:

$$\frac{dm_i^S}{dv_1} - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)\frac{dm_i^S}{dv_1} = 2m_i^S(1 - m_i^S)m_i^S$$

$$\left[1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)\right]\frac{dm_i^S}{dv_1} = 2m_i^S(1 - m_i^S)m_i^S$$

$$\frac{dm_i^S}{dv_1} = \frac{2m_i^S(1 - m_i^S)m_i^S}{1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)} \tag{IA.4}$$

Substitute (IA.4) back into (IA.1):

$$\frac{dS_i}{dv_1} = m_i^S + (v_1 + v_2 K_a)\frac{2m_i^S(1 - m_i^S)m_i^S}{1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)}$$

$$\frac{dS_i}{dv_1} = m_i^S\left[1 + \frac{2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)}{1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)}\right]$$

$$\frac{dS_i}{dv_1} = m_i^S\left[\frac{1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S) + 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)}{1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)}\right]$$

$$\frac{dS_i}{dv_1} = \frac{m_i^S}{1 - 2(v_1 + v_2 K_a)m_i^S(1 - m_i^S)} \tag{IA.5}$$

B. Cleaning Text Data of Green Certificates and Building Permits

Step 1: Text Extraction from Certification Reports and Building Permits
I begin by using the python package PdfReader to extract the text page by page for the certification reports (downloaded from the GBR website) and building permit descriptions.
Step 2: Text Pre-processing and Cleaning
To ensure consistency and remove noise, the extracted text from the certification reports and building permit descriptions undergoes a rigorous pre-processing and cleaning process:

- Expanding Contractions: Contractions are expanded using the python contractions library (e.g., “can't” is expanded to “cannot”).
- Removing URLs: URLs are identified and removed using regular expressions.
- Normalizing Numerical Expressions: Dollar signs are standardized by replacing them with the word "dollar" while preserving the numerical value (e.g., “$2,500” to “2,500 dollar”). Similarly, percentage signs are replaced with the text “percent” while retaining the numerical component. Numeric ranges, such as “2–6%”, are reformatted to a more readable form (e.g., “2 to 6 percent”).
- Removing Punctuation and Special Characters: Punctuation and special characters are removed.
- Removing Program-Specific Phrases: Specific program names that do not contribute to the analysis are removed using regular expressions. For instance, phrases like “home energy score” are targeted and removed.
- Tokenization: The text is tokenized into individual words using NLTK's word_tokenize function.
- Removing Stopwords: Common English stopwords (e.g., “the”, “and”, “is”) are removed using a predefined list from NLTK.
- Lemmatization: Words are lemmatized using WordNetLemmatizer (e.g., “running” becomes “run”).
- Frequency-Based Filtering: Words that appear frequently across all documents but do not add significant meaning are identified and removed. Specifically, the top 10% of the most frequent words are filtered out.

- Reassembling Cleaned Text: After all cleaning steps, the processed words are reassembled into single strings for each document.

Step 3: Data Preparation for Similarity Calculation
After the text has been cleaned and standardized, the following steps are undertaken to prepare the data for similarity calculations:

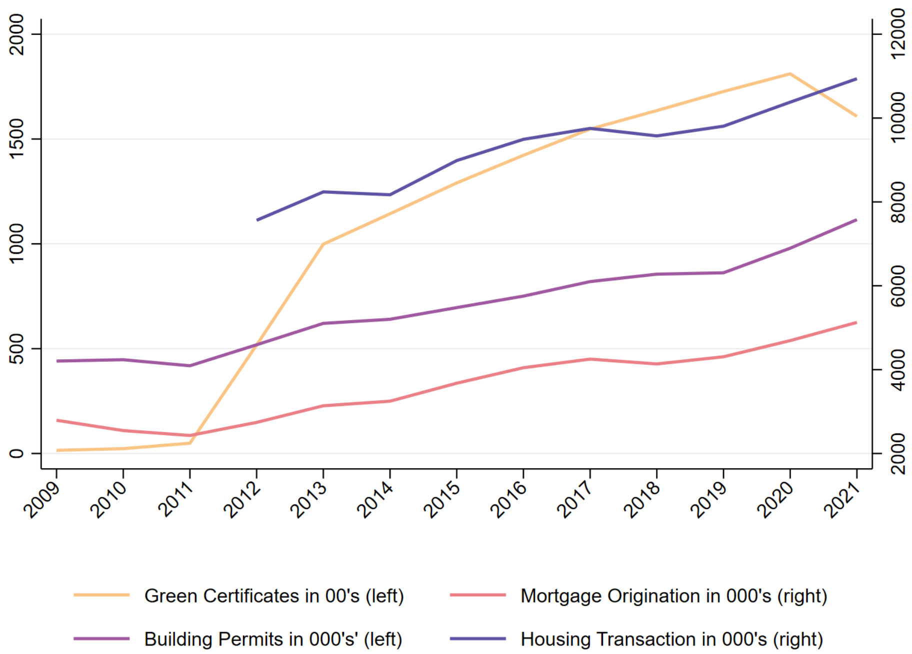
- Combining Text from Multiple Pages: For each certification report, text from the first six pages is combined. This aggregation ensures that the most relevant content of each document is captured comprehensively.

- Matching Records: The cleaned text data is matched with both the focal and neighboring properties in the "focal×neighbor" certificate or permit level panel, as constructed in Section V.B.2.

Step 4: Text Similarity Calculation
With the cleaned text data prepared, text similarity calculations for the focal and neighboring property are performed using cosine similarity. A TF-IDF (Term Frequency-Inverse Document Frequency) Vectorizer is initialized to convert the text into numerical vectors, capturing the importance of terms in the context of each document. Cosine similarity measures the cosine of the angle between two vectors, providing a metric of similarity that ranges from 0 (completely dissimilar) to 1 (identical).

C. Supplementary Figures and Tables

(A) Green Certifications and Housing Market Over Time



(B) Spatial Distribution of Green Certified Single-Family Homes

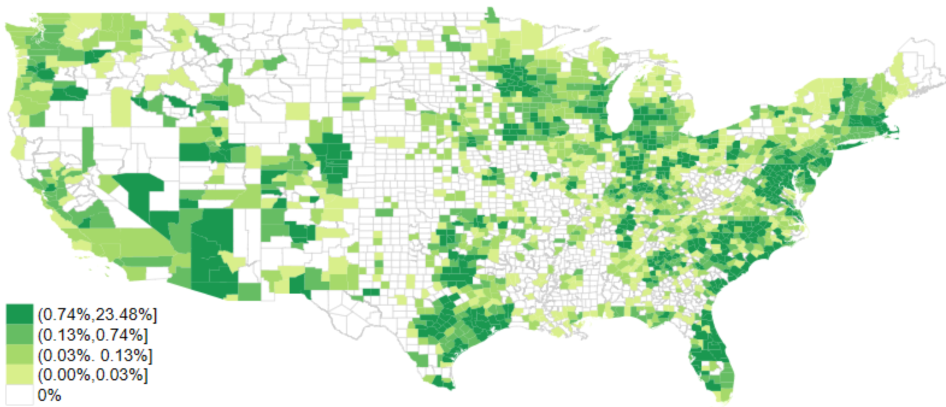
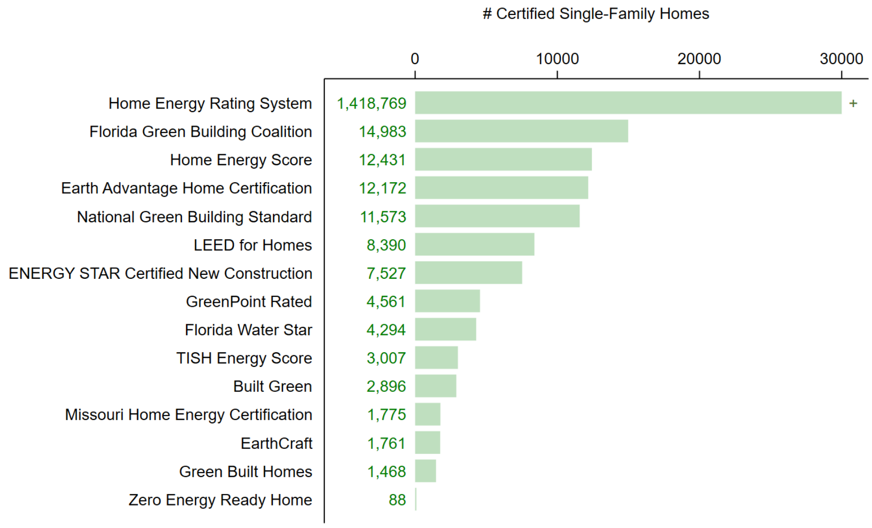


Figure IA.1. Trends in Residential Green Certification in the US. Panel A plots the number of new green certified single-family homes, new privately-owned single-family homes authorized in permit-issuing places, new home purchase mortgage origination and single-family home transactions in the United States from 2009 to 2021. Green certificates and building permits are represented on the left axis. Mortgage origination and housing transactions are plotted on the right axis. Panel B shows on the map of the contiguous US the percentage of single-family homes in the sample counties that are green certified as of 2022.

(A) Distribution of Residential Green Certification Programs



(B) Utility Savings and HERS Scores

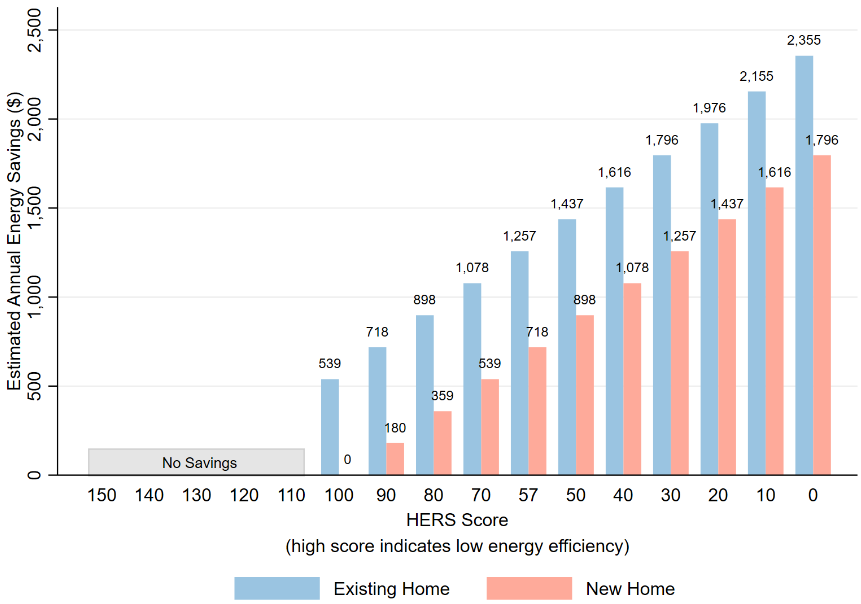
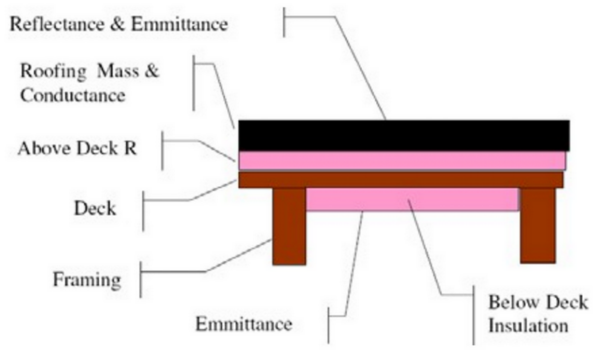


Figure IA.2. Institutional Details of Residential Green Certification Programs. Panel A shows the number of single-family homes certified under major green certification programs as of 2022. Panel B plots the estimated annual energy savings for different Home Energy Rating System (HERS) scores. The data for this panel was extracted on August 17, 2024, from www.hersindex.com/hers-index/interactive-hersindex/interactive-hersindex-inside/.

(A) Inspection Specifications for Roof Deck above Attic



(B) Illustration of Blower Door Test

Figure IA.3. Examples of Green Certification Technical Standards. This figure shows two examples of green certification technical standards. Panel A illustrates the specifications in inspecting the roof deck above the attic as part of the on-site inspection procedures for California HERS Ratings. Panel B displays an example of the blower door test inspection.

(A) Certification Steps for Contractors under Built Green Program

(B) A Homeowner Sharing Experience of Green Certification Process

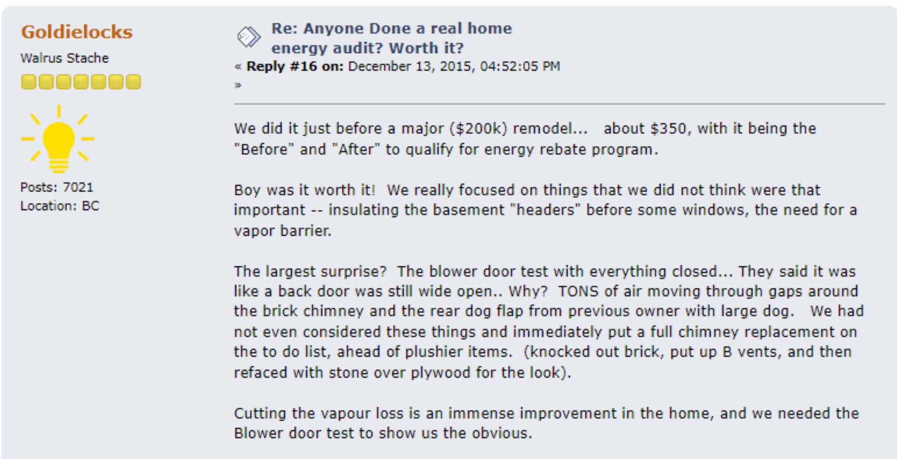
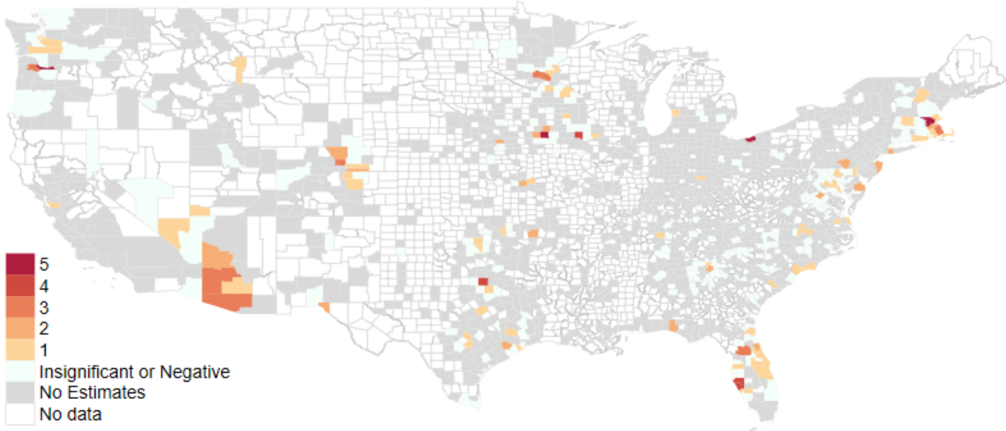


Figure IA.4. Examples of Green Certification Steps. Panel A shows an example of the steps a home contractor needs to follow to certify a home under Built Green program. Panel B shows an example of a post on an online forum by a homeowner sharing experience of green certification and energy rebates (link).

(A) Spatial Distribution of Green Certification Premium



(B) Distribution of Estimated Green Certification Premium and *t*-Statistics

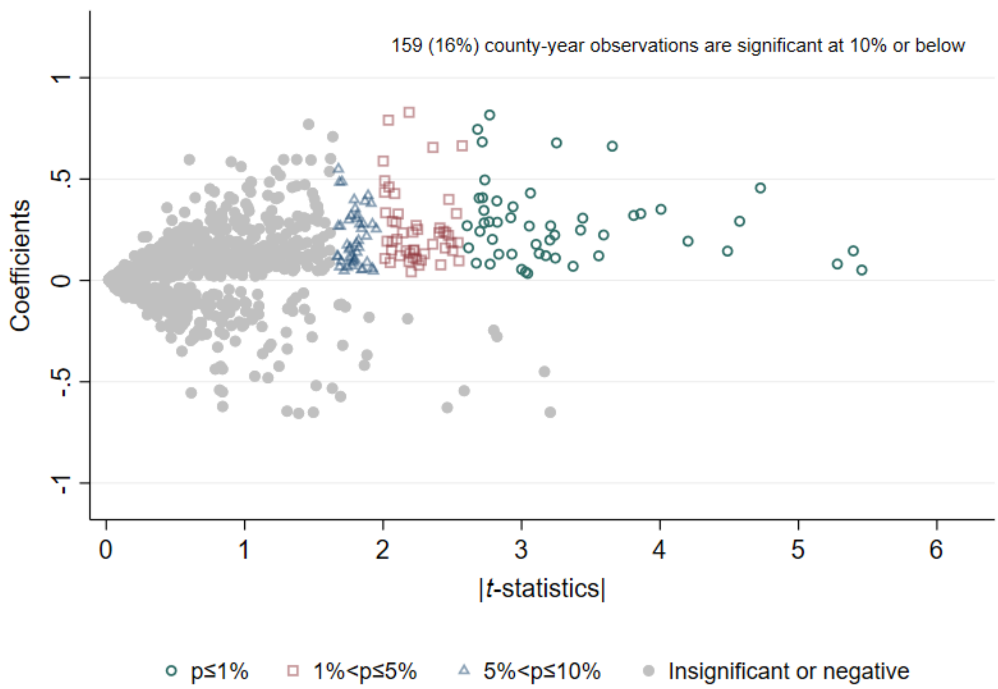


Figure IA.5. County-Year-Level Green Certification Premium in House Prices. Panel A shows the spatial distribution of the premiums for green-certified homes estimated for each county and year using hedonic regressions of log transaction prices of single-family homes on property and mortgage characteristics and zip code fixed effects. The regression equation is $y_{it} = \alpha + \beta\ Green_{it} + \gamma\ Control_{it} + \theta_z + \epsilon_{it}$. The control variables include property age, living area, # bedrooms, exterior materials, heat type, roof materials, a 0/1 indicator of mortgage-financed purchase, mortgage term, mortgage interest rate. The color intensity in Panel A represents the number of years (from 2018 to 2022) for which the β is positive and statistically significant at the 10% level or below. Panel B plots the βs and associated t-statistics estimated in Panel A.

Table IA.I
Green Certification Programs

This table reports the overview of 15 green certification programs. It includes their geographic coverage, attributes evaluated in their programs, and whether they mandate the use of green contractors under the program. Column (4) reports the threshold scores (or rating categories) used in this paper to define whether a property is green certified (Green) under respective programs.

Program	Coverage (1)	Attributes Evaluated (2)	Green Contractors Required (3)	Green Threshold (4)
Built Green	King County, WA Snohomish County, WA	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Single-family: > 3-star Remodeling: > 2-star, 20/20 Refit Challenge, Refit
ENERGY STAR Certified New Construction	National	Energy Efficiency	Yes	Certified
Earth Advantage® Certifications	Northwest	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
EarthCraft	Greater Atlanta Area	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
Florida Green Building Coalition	Florida	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
Florida Water Star	St Johns River Water Management District	Water	Not Necessary	Certified
Green Built Homes	North Carolina	Energy, Site, Water, Indoor Air Quality, Materials	Yes	Certified
GreenPoint Rated	California	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Not Necessary	≥ 50 points
Home Energy Rating System	National	Energy Efficiency	Not Necessary	< 100
Home Energy Score	National	Energy Efficiency	Not Necessary	> 5
LEED for Homes	National	Energy, Site, Water, Indoor Air Quality, Materials	Yes	Certified
Missouri Home Energy Certification	Missouri	Energy Efficiency	Not Necessary	Certified
National Green Building Standard	National	Energy, Site, Water, Indoor Air Quality, Materials, Operation	Yes	Certified
TISH Energy Score	Minneapolis Bloomington	Energy Efficiency	Not Necessary	> 85
Zero Energy Ready Home	National	Energy, Water, Indoor Air Quality	Yes	Certified

Table IA.II
Peer Effects of Green Neighbors on Residential Green Investments - Including Controls

This table replicates column (3) of Table II by adding property and neighborhood controls following equation (23). The sample includes observations for which all control variables have non-missing values. The property controls include property age, living area, # bedrooms, exterior materials, heat type and roof materials. The neighborhood controls include residential housing density and annual housing price growth at census tract level, AGI ($1,000) per capita at zip code level, number of regulatory green incentive programs, % climate worried at county level, and the proportion of green homes within a ring d = 0.1, 0.3 and 0.5 miles. The property and neighborhood controls are defined in Table I. All models include zip code and year-quarter fixed effects. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10000)			
	(1)	(2)	(3)	(4)
$N_G(\leq 0.1$ mi)	0.66***	0.66***	0.47***	0.47***
	(0.14)	(0.14)	(0.12)	(0.12)
$N_G(\leq 0.3$ mi)	0.17***	0.17***	0.17***	0.17***
	(0.02)	(0.02)	(0.03)	(0.03)
$N_G(\leq 0.5$ mi)	0.03***	0.03***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Property controls	N	Y	N	Y
Neighborhood controls	N	N	Y	Y
Fixed effects	Zip code, YQ	Zip code, YQ	Zip code, YQ	Zip code, YQ
R^2 (Adj.)	0.0026	0.0026	0.0028	0.0028
Observations	170,708,293	170,708,293	170,708,293	170,708,293

Table IA.III
Peer Effects in Subsamples of High and Low Housing Supply Constraints

Columns (1) and (3) of this table show the baseline estimates of Table II in the subsample of properties in above-median regulatory restrictiveness (potential seller's) markets, and columns (2) and (4) shows the same in the subsample of properties in below-median regulatory restrictiveness (potential buyer's) markets. The bottom row in the column header denotes the version of WRLURI. The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring d = 0.1, 0.3 and 0.5 miles. All the models include zip code and year-quarter fixed effects. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)			
	(1)	(2)	(3)	(4)
Housing Supply Constraints:	High	Low	High	Low
[WRLURI Version:]	[2006]	[2006]	[2018]	[2018]
$N_G(\leq 0.1$ mi)	0.59***	0.57***	0.46***	0.42***
	(0.11)	(0.09)	(0.06)	(0.08)
$N_G(\leq 0.3$ mi)	0.23***	0.16***	0.33***	0.21***
	(0.02)	(0.02)	(0.04)	(0.02)
$N_G(\leq 0.5$ mi)	0.03***	0.06***	0.07***	0.05***
	(0.01)	(0.02)	(0.01)	(0.01)
Fixed effects	Zip code, YQ	Zip code, YQ	Zip code, YQ	Zip code, YQ
R^2 (Adj.)	0.0032	0.0017	0.0018	0.0028
Observations	223,231,911	208,599,408	483,002,288	321,170,238

Table IA.IV
Baseline Estimates for Subsample of Green Homes with Verified Ex-Ante Investments

This table shows the baseline estimates of Table II for the subsample of green homes with verified investments occurring within one year prior to the green certification date, where verified investments are proxied by building permits. The regression specification is from equation (22). The outcome variable *Green (=10,000)* is an indicator taking the value of 10,000 in the quarter a household obtains the first green certificate for his/her property. $N_G(\leq d\ mi)$ is the green exposure measured as the number of neighbors who have obtained green certificates over quarters $t-3$ to t and are located within a ring $d = 0.1$, 0.3 and 0.5 miles. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green (=10,000)		
	(1)	(2)	(3)
$N_G(\leq 0.1$ mi)	0.32***	0.34***	0.34***
	(0.07)	(0.07)	(0.07)
$N_G(\leq 0.3$ mi)	0.13***	0.10***	0.09***
	(0.02)	(0.02)	(0.02)
$N_G(\leq 0.5$ mi)	0.02**	0.02**	0.02*
	(0.01)	(0.01)	(0.01)
Fixed effects	N	Zip code, YQ	Zip code × YQ
R^2 (Adj.)	0.0004	0.0007	0.0015
Observations	81,757,257	81,757,254	81,751,343

Table IA.V
Placebo Test: Peer Effects of Exposure to Inefficient Green Certifications

This table shows the baseline estimates of Table II in a sample of focal households whose green exposures arise exclusively from neighbors for whom the green certification processes revealed that their homes' efficiency were lower than that of an average home (inefficient green certificates). The outcome variable *Green* (=*10,000*) is an indicator taking the value of 10,000 in the quarter a focal household obtains the first inefficient green certificate for his/her property. The green threshold for each program is defined in Table IA.I. $N_G(\leq d\ mi)_{\boldsymbol{Placebo}}$ is the exposure measured as the number of neighbors who have obtained inefficient green certificates over quarters $t-3$ to t and are located within a ring $d = 0.1$, 0.3 and 0.5 miles. Standard errors are clustered by zip code×year-quarter and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Outcome: Green $(=10{,}000)_{\text{Placebo}}$		
	(1)	(2)	(3)
$\text{N}_G(\leq 0.1\text{ mi})_{\text{Placebo}}$	1.43	1.47	1.17
	(2.66)	(2.75)	(2.81)
$\text{N}_G(\leq 0.3\text{ mi})_{\text{Placebo}}$	-1.60	-1.43	-1.66
	(1.63)	(1.71)	(1.78)
$\text{N}_G(\leq 0.5\text{ mi})_{\text{Placebo}}$	2.22*	1.20	1.05
	(1.25)	(1.28)	(1.24)
Fixed effects	N	Zip code, YQ	Zip code × YQ
R^2 (Adj.)	0.0000	0.0023	0.0075
Observations	907,382,917	907,382,912	907,372,314

Table IA.VI
Policy Implications: Peer Effects and Provision of Regulatory Incentives

This table reports the results of Poisson pseudo-maximum-likelihood cross-sectional regression of the number of regulatory incentives on the strength of local community interactions. The outcome variable in columns (1) and (2) (columns (3) and (4)) is the mean (median) of the number of county- and state-level regulatory green incentives in a county over 2018 and 2022. Social connectedness and social capital are defined in Section V.B.3. *Housing mkt. & demog. controls* are the mean (median) over 2018 and 2022 of house price index, population, per capita income, GDP growth, median age, and the percentage of people aged 25 and above with at least a college degree in columns (1) and (2) (columns (3) and (4)). All the models include state fixed effects. Standard errors are clustered by state and reported in parentheses. *, ** and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Outcome:	Mean # Incentives		Median # Incentives	
	(1)	(2)	(3)	(4)
Social Connectedness	0.007		0.009	
	(0.01)		(0.01)	
Social Capital		0.002		0.002
		(0.00)		(0.00)
Housing mkt. & demog. controls	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y
R^2	0.4330	0.4330	0.4254	0.4254
Observations	2,514	2,514	2,514	2,514